

The performance impact of I/O optimizations and disk improvements

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In this paper, we use real server and personal computer workloads to systematically analyze the true performance impact of various I/O optimization techniques, including read caching, sequential prefetching, opportunistic prefetching, write buffering, request scheduling, striping, and short-stroking. We also break down disk technology improvement into four basic effects—faster seeks, higher RPM, linear density improvement, and increase in track density—and analyze each separately to determine its actual benefit. In addition, we examine the historical rates of improvement and use the trends to project the effect of disk technology scaling. As part of this study, we develop a methodology for replaying real workloads that more accurately models I/O arrivals and that allows the I/O rate to be more realistically scaled than previously. We find that optimization techniques that reduce the number of physical I/Os are generally more effective than those that improve the efficiency in performing the I/Os. Sequential prefetching and write buffering are particularly effective, reducing the average read and write response time by about 50% and 90%, respectively. Our results suggest that a reliable method for improving performance is to use larger caches up to and even beyond 1% of the storage used. For a given workload, our analysis shows that disk technology improvement at the historical rate increases performance by about 8% per year if the disk occupancy rate is kept constant, and by about 15% per year if the same number of disks are used. We discover that the actual average seek time and rotational latency are, respectively, only about 35% and 60% of the specified values. We also observe that the disk head positioning time far dominates the data transfer time, suggesting that to effectively utilize the available disk bandwidth, data should be reorganized such that accesses become more sequential.

1. Introduction

Because of the slow mechanical nature of many storage devices, the importance of optimizing I/O operations has been well recognized. As a result, a plethora of optimization techniques including caching, write buffering, prefetching, request scheduling, and parallel I/O have been invented. The relative effectiveness of these techniques, however, is not clear because they have been studied in isolation by different researchers using different methodologies. Furthermore, because many of the techniques have not been evaluated with real workloads,

their actual effect is not known. Some of the ideas have been proposed or implemented, but few or no performance results have been published (e.g., opportunistic prefetching). As the performance gap between the processor and disk-based storage continues to widen [1, 2], increasingly aggressive optimization of the storage system is needed, and this requires a good understanding of the real potential of the various I/O optimization techniques and how they work together. In this paper, we systematically investigate how the different techniques affect actual performance by using trace-driven

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simulations with a large set of traces gathered from a wide range of real-world settings, including both server and personal computer (PC) environments. To make our findings more broadly applicable, we focus on general rules of thumb about what can be expected from each of these techniques rather than precise quantification of improvement for a particular workload and a specific implementation.

Tremendous efforts have also gone into improving the underlying technology of disks. The improvement in disk technology is usually quantified by using physical metrics, such as the tracks or bits per inch, the average seek time, and the rotational speed. Relating physical metrics like these to the performance delivered to real workloads is, however, difficult. Thus, it is not apparent how an improvement in one metric compares with an improvement in another in terms of their real-world impact. Furthermore, some of the metrics are not focused on performance but have a significant effect on it. For example, increasing the recording density could improve performance because, if the bits are packed more closely together, they can be accessed with a smaller physical movement. In this paper, we break down the steady improvements in disk technology into four major basic effects: seek time reduction resulting from actuator improvement, increase in rotational speed, linear density improvement, and increase in track density. Then we separately analyze each one to determine its effect on real workloads. We also examine the historical rates of improvement and use the trends to project the actual performance improvement that can be expected from disk technology scaling.

In a companion paper [3], we analyze in detail the characteristics of the various workloads we use, specifically 1) the I/O intensity of the workloads and the overall significance of I/O in the workloads; 2) how the I/O load varies over time and how it behaves when aggregated; and 3) the interaction of reads and writes and how it affects performance. Although the current paper is self-contained, readers are encouraged to also read the companion paper to better understand the workloads on which this analysis is based. The insights gained from the current study motivated the idea of automatic locality-improving storage (ALIS) [4], which is a storage system that continually monitors the way it is accessed and then automatically reorganizes selected disk blocks so that accesses become effectively more sequential. In fact, the results we derive here serve as the baseline for the analysis of ALIS in [4]. Therefore, this paper has an emphasis on the optimizations that directly affect ALIS—in particular, the prefetching.

The remainder of this paper is organized as follows. Section 2 contains a brief overview of previous work in evaluating I/O optimization techniques. Section 3 discusses

our methodology and describes the traces that we use. In Section 4, we analyze the effect of the various optimization techniques. In Section 5, we consider the real impact of disk technology improvement over time. Section 6 concludes and summarizes this paper. Because of the huge amount of data that is involved in this study, we can present only a characteristic cross section here. More detailed graphs and data are available in [5].

2. Related work

Various I/O optimization techniques have been individually evaluated by different researchers using dissimilar methodologies including discrete event simulation and analytical modeling. In some cases, the simulations are based on traces of real workloads and in others, randomly generated synthetic workloads. For instance, disk caching is extensively analyzed in [6, 7], prefetching in [8, 9], write buffering in [10, 11], request scheduling in [12–14], and striping in [15, 16]. At the logical level, caching, prefetching, and write buffering are well covered in [17, 18]. Several researchers have also explored ways to improve the various techniques in special situations where the reference pattern is known ahead of time (e.g., [19]). Because improving I/O performance is important, there has been a lot of research on I/O optimization techniques. We mention only some of the more recent work. The reader is referred to [20] for a comprehensive survey of early work on I/O optimization.

3. Methodology

The methodology used in this paper is *trace-driven simulation* [21, 22]. In trace-driven simulation, relevant information about a system is collected while the system is handling the workload of interest. This is referred to as *tracing the system* and is usually achieved by using hardware probes or by adding instrumentation to the software. In the second phase, the resulting trace of the system is played back to drive a model of the system under study. Trace-driven simulation is thus a form of event-driven simulation in which the events are taken from a real system that is operating under conditions similar to the ones being simulated. A common difficulty in using trace-driven simulations to study I/O systems is to realistically model timing effects, specifically to account for events that occur faster or slower in the simulated system than in the original system. This difficulty arises because information about how the arrival of subsequent I/Os depends upon the completion of previous requests cannot be easily extracted from a system and recorded in the traces. As described below, we create and use a new method for replaying I/O traces that more accurately models the timing of I/O arrivals and that allows the I/O rate to be more realistically scaled (e.g., when processor power is increased) than previous practice.

Modeling timing effects

In general, simulation models used to evaluate storage system performance can be broadly classified into open and closed models, depending on how request arrivals are choreographed. The closed model traditionally maintains a constant population of outstanding requests. Whenever a request is completed, a new request is issued in its place, sometimes after a simulated “think” time. These models essentially assume that all of the I/Os are time-critical [23], so that a new I/O is issued only after a previous request is completed. By maintaining a constant population of outstanding requests, these models effectively smooth out any burstiness in the I/O traffic. Such an approach is clearly not representative of real workloads, which have been shown in several studies (e.g., [3]) to have bursty I/O traffic patterns.

In the open model, requests arrive at predetermined times (e.g., traced time in [24] and traced interarrival time scaled by a constant factor in [14]), independently of the performance of the storage system. Such models assume that the workload consists exclusively of time-noncritical requests [23], so that whether a preceding request is completed has no bearing on when the system is able to issue subsequent I/Os. Again, this is clearly not true in real systems, in which an overloaded storage system, by being slow, automatically exerts back pressure on the processes generating the I/Os. For example, 66–91% of the I/Os are flagged as synchronous in PC workloads [3] and 52–74% in UNIX** workloads [25]. In other words, the system generally has to wait for I/Os to be completed before it can continue with subsequent processing. Such data highlights the importance of accounting for the feedback effect between request completion and subsequent request issuance. From a practical perspective, having a feedback mechanism also ensures that the number of outstanding requests will not grow without bound whenever the storage system is unable to handle the incoming workload.

Modeling the feedback effect and thereby limiting the number of outstanding requests is especially helpful in this study because we have a diverse set of workloads collected over the span of several years and a wide range of experiments in which the performance of the storage system is significantly varied. Some of our experiments evaluate techniques that are opportunistic; i.e., they take advantage of idle time. Therefore, we have to account for the burstiness seen in real I/O traffic. With these requirements in mind, we came up with a methodology designed to incorporate feedback between request completion and subsequent I/O arrivals, and model burstiness.

Results in [3] show that there is effectively little multiprocessing in PC workloads and that most of the I/Os are synchronous. Such predominantly single-process

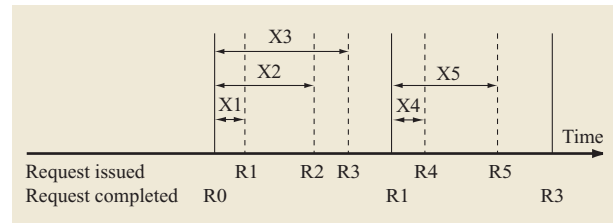


Figure 1

Intervals between issuance of I/O requests and most recent request completion.

workloads can be modeled by assuming that after completing an I/O, the system has to do some processing and the user some “thinking” before the next set of I/Os can be issued. For instance, in the timeline in **Figure 1**, after request R0 is completed, there are delays during which the system is processing and the user is thinking before requests R1, R2, and R3 are issued. Because R1, R2, and R3 are issued after R0 has been completed, we consider them to be dependent on R0. Similarly, R4 and R5 are deemed to be dependent on R1. Presumably, if R0 is completed earlier, R1, R2, and R3 will be dragged forward and issued earlier. If this in turn causes R1 to be finished earlier, R4 and R5 will be similarly moved forward in time. The “think” time between the completion of a request and the issuance of its dependent requests can be adjusted to speed up or slow down the workload. In short, we consider a request to be dependent on the *last* completed request, and we issue a request only after its parent request has completed. For multiprocessing workloads, this dependence relationship should be maintained on a per-process basis, but unfortunately process information is not always available in I/O traces. To account for multiprocessing workloads, we merge multiple traces to form a workload with several independent streams of I/O, each obeying the dependence relationship described above.

In essence, we have built an out-of-order multiple-issue machine that tries to preserve the dependency structure between I/O requests. We maintain an issue window of 64 requests. A request within this window is issued when the request on which it is dependent completes and the think time has elapsed. Inferring the dependencies based on the last completed request is the best we can do given the block-level traces we have. If the workloads were completely described using logical and higher-level system events (e.g., system calls and interrupts), we might be able to more accurately model feedback effects using a system-level model (e.g., [23]). In the limit, we can run the workloads on a system simulator where we have control over the timing of events [26] or on a virtual machine

[27] or on a real system with a timing-accurate storage emulator [28]. However, getting real users to release traces of reference address is difficult enough. Asking them for logical data about their computer operations is next to impossible. Moreover, “capturing” a workload so that it can be realistically replayed may be relatively easy for batch jobs, but it is very difficult for interactive workloads. We essentially end up with the same problem of having to decide what happens when the system reacts faster. For instance, will the user click the mouse earlier?

Workloads and traces

The traces analyzed in this study were collected from both server and PC systems running real user workloads on three different platforms—Microsoft Windows NT**, IBM AIX*, and HP-UX**. All of them were collected downstream of the database buffer pool and the file system cache. Thus, these are *real* I/O traces, not logical ones. The PC traces were collected by using VTrace [29], a software tracing tool for Intel** x86 PCs running Windows NT/2000**. In this study, we are primarily interested in the disk activities, which are collected by VTrace through the use of device filters. We have verified the disk activity collected by VTrace with the raw traffic observed by a bus (SCSI) analyzer. Both the IBM AIX and HP-UX traces were collected using kernel-level trace facilities built into the respective operating systems. Most of the traces were gathered over periods of several months, but to keep the simulation time manageable, we use only the first 45 days of the traces, of which the first 20 days are used to warm up the simulator.

The PC traces were collected from the primary systems of a wide variety of users, including engineers, graduate students, a secretary, and several people in senior managerial positions. Because we have a wide variety of users in our sample, we believe that our traces are illustrative of the PC workloads in many offices, especially those involved in research and development. Note, however, that the traces should not be taken as typical or representative of any other system or environment. Despite this disclaimer, the fact that many of their characteristics correspond to those obtained previously (see [3]), albeit in somewhat different environments, suggest that our findings can, to a large extent, be generalized. **Table 1(a)** summarizes the characteristics of these traces. We denote the PC traces as P1, P2, ..., P14 and the arithmetic mean of their results as *P-Avg*. As detailed in [3], the PC traces contain only I/Os that occur when the user is actively interacting with the system. Specifically, we consider the system to be idle from ten minutes after the last user keyboard or mouse activity until the next such user action, and we assume that there is no I/O activity during the idle periods. We believe that this is a reasonable approximation in the PC environment,

although it is possible that we are ignoring some level of activity resulting from periodic system tasks such as daemons. This latter type of activity should have a negligible effect on the I/O load, and is not likely to be noticed by the user.

The servers traced include a file server, a time-sharing system, and a database server. The characteristics of these traces are summarized in **Table 1(b)**. Throughout this paper, we use the term *S-Avg*. to denote the arithmetic mean of the results for these server workloads. The first file server trace (FS1) was taken off a file server for nine clients at the University of California, Berkeley. This system was primarily used for compilation and editing. It is referred to as *Snake* in [25]. The trace denoted TS1 was gathered on a time-sharing system at an industrial research laboratory. It was mainly used for news, mail, text editing, simulation, and compilation. It is referred to as *Cello* in [25]. The database server trace (DS1) was collected at one of the largest health insurers in the nation. The system traced was running an enterprise resource planning (ERP) application on top of a commercial database system. This trace is only seven days long, and the first three days are used to warm up the simulator. More details about the traces and how they were collected can be found in [3].

In addition to these base workloads, we scale up the traces to obtain workloads that are more intense. Results reported in [3] show that for the PC workloads, the processor utilization during the intervals between the issuance of an I/O and the last I/O completion is related to the length of the interval by a function of the form $f(x) = 1/(ax + b)$, where $a = 0.0857$ and $b = 0.0105$. To model a processor that is n times faster than the one in the traced system, we would scale only the system processing time by n , leaving the user portion of the think time unchanged. Specifically, we would replace an interval of length x with one of length $x[1 - f(x) + f(x)/n]$. In this paper, we run each workload preserving the original think time. For the PC workloads, we also evaluate what happens in the limit when systems are infinitely fast; i.e., we replace an interval of length x with one of $x[1 - f(x)]$. We denote these speeded-up PC workloads as P1s, P2s, ..., P14s and the arithmetic mean of their results as *Ps-Avg*.

We also merge ten of the longest PC traces to obtain a workload with ten independent streams of I/O, each of which obeys the dependence relationship discussed above. We refer to this merged trace as *Pm*. The volume of I/O traffic in this merged PC workload is similar to that of a server supporting multiple PCs. However, its locality characteristics are different because there is no sharing of data among the different users, so that if two users are both using the same application, they end up using different copies of the application. *Pm* might be construed as the workload of a system on which multiple

Table 1 Trace descriptions.

(a) Personal systems											
Designation	User type	System configuration					Trace characteristics				
		System (MHz)	Memory (MB)	File systems (GB)	Storage used ⁱ (GB)	No. disks	Duration	Footprint ^{iv} (GB)	Traffic (GB)	Requests ($\times 10^6$)	R/W ratio
P1	Engineer	333 P6	64	1 GB FAT ⁱⁱ 5 GB NTFS ⁱⁱⁱ	6	1	45 days (7/26/99–9/8/99)	0.945	17.1	1.88	2.51
P2	Engineer	200 P6	64	1.2, 2.4, 1.2 GB FAT	4.8	2	39 days (7/26/99–9/2/99)	0.509	9.45	1.15	1.37
P3	Engineer	450 P6	128	4, 2 GB NTFS	6	1	45 days (7/26/99–9/8/99)	0.708	5.01	0.679	0.429
P4	Engineer	450 P6	128	3, 3 GB NTFS	6	1	29 days (7/27/99–8/24/99)	4.72	26.6	2.56	0.606
P5	Engineer	450 P6	128	3.9, 2.1 GB NTFS	6	1	45 days (7/26/99–9/8/99)	2.66	31.5	4.04	0.338
P6	Manager	166 P6	128	3, 2 GB NTFS	5	2	45 days (7/23/99–9/5/99)	0.513	2.43	0.324	0.147
P7	Engineer	266 P6	192	4 GB NTFS	4	1	45 days (7/26/99–9/8/99)	1.84	20.1	2.27	0.288
P8	Secretary	300 P5	64	1, 3 GB NTFS	4	1	45 days (7/27/99–9/9/99)	0.519	9.52	1.15	1.23
P9	Engineer	166 P5	80	1.5, 1.5 GB NTFS	3	2	32 days (7/23/99–8/23/99)	0.848	9.93	1.42	0.925
P10	CTO	266 P6	96	4.2 GB NTFS	4.2	1	45 days (1/20/00–3/4/00)	2.58	16.3	1.75	0.937
P11	Director	350 P6	64	2, 2 GB NTFS	4	1	45 days (8/25/99–10/8/99)	0.73	11.4	1.58	0.831
P12	Director	400 P6	128	2, 4 GB NTFS	6	1	45 days (9/10/99–10/24/99)	1.36	6.2	0.514	0.758
P13	Grad. student	200 P6	128	1, 1, 2 GB NTFS	4	2	45 days (10/22/99–12/5/99)	0.442	6.62	1.13	0.566
P14	Grad. student	450 P6	128	2, 2, 2, 2 GB NTFS	8	3	45 days (8/30/99–10/13/99)	3.92	22.3	2.9	0.481
P-Avg.	—	318	109	—	5.07	1.43	41.2 days	1.59	13.9	1.67	0.816
(b) Servers											
Designation	Primary function	System configuration					Trace characteristics				
		System	Memory (MB)	File systems	Storage used (GB)	No. disks	Duration	Footprint ^{iv} (GB)	Traffic (GB)	Requests ($\times 10^6$)	R/W ratio
FS1	File server (NFS ^v)	HP 9000/720** (50 MHz)	32	3 BSD** FFS ^{viii} (3 GB)	3	3	45 days (4/25/92–6/8/92)	1.39	63	9.78	0.718
TS1	Time-sharing system	HP 9000/877** (64 MHz)	96	12 BSD FFS (10.4 GB)	10.4	8	45 days (4/18/92–6/1/92)	4.75	123	20	0.794
DS1	Database server (ERP ^{vi})	IBM RS/6000* R30 SMP ^{vii} (4 $\times$ 75 MHz)	768	8 AIX* JFS ^{ix} (9 GB), 3 paging (1.4 GB), 30 raw database partitions (42 GB)	52.4	13	7 days (8/13/96–8/19/96)	6.52	37.7	6.64	0.607
S-Avg.	—	—	299	—	18.5	8	32.3 days	4.22	74.6	12.1	0.706

ⁱ Sum of all file systems and allocated volumes
ⁱⁱ File allocation table
ⁱⁱⁱ Microsoft NTFS
^{iv} Amount of data referenced at least once
^v Sun Microsystems Network File System**
^{vi} Enterprise resource planning
^{vii} Symmetric multiprocessor
^{viii} Wind River Systems BSD fast file system
^{ix} IBM AIX journal file system

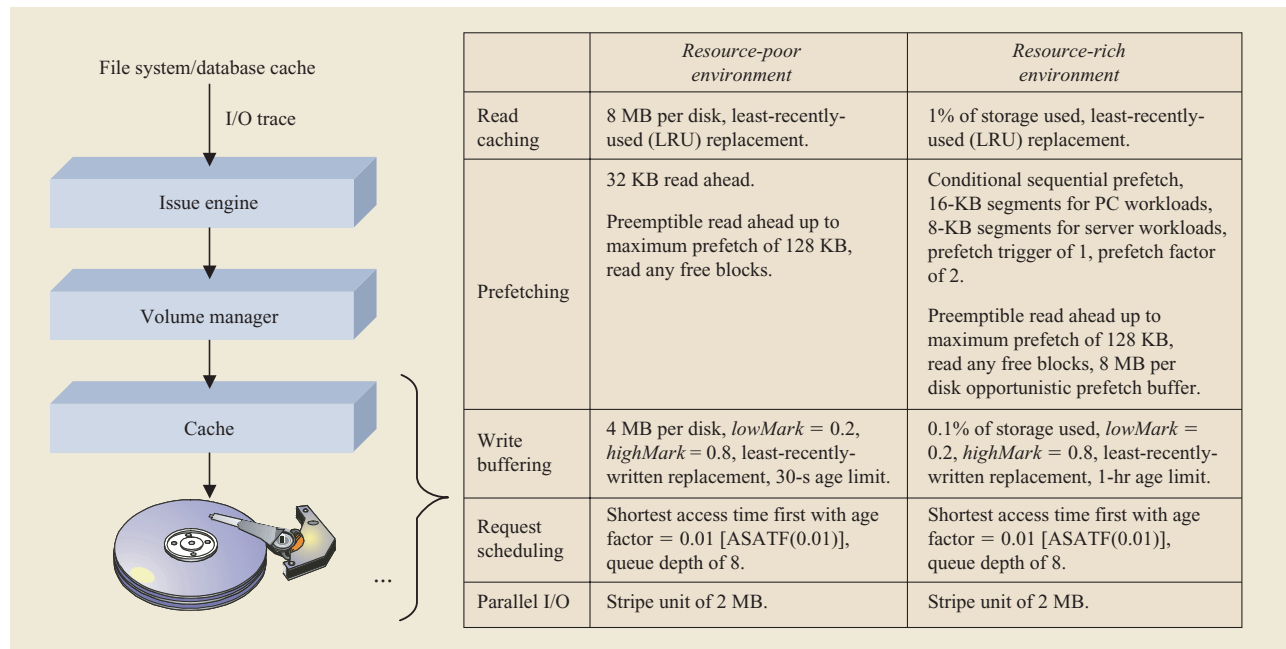


Figure 2

Block diagram of simulation model showing the base configurations and default parameters used to evaluate the various I/O optimization techniques and disk improvements. The parameters pertaining to each technique are described in detail in Section 4.

independent PC workloads are consolidated. For the server workloads, we merge the FS1 and TS1 traces to obtain another trace which we denote as *Sm*. Note that neither method for scaling up the workloads is perfect, but we believe that they are more realistic than simply scaling the interarrival time, as is commonly done. In this paper, we often use the term *PC workloads* to refer collectively to the base PC workloads, the speeded-up PC workloads, and the merged PC workload. The term *server workloads* likewise refers to the base server workloads and the merged server workload.

Simulation model

The major components of our simulation model are presented in **Figure 2**. In practice, optimizations such as caching, prefetching, write buffering, request scheduling, and striping may be performed at multiple levels in the storage system. For instance, there may be several outboard storage controllers, storage adapters (host bus adapters), and disk drives, and they may all perform some of the optimizations to some extent. The number of combinations of which does what and to what extent is large, and the interaction among the optimizations performed at the various levels is complicated and obscure. To gain fundamental insights into the

effectiveness of each of the optimizations, we collapse the different levels and model each of the optimizations once.

For example, we model only a single level of cache instead of a disk-drive cache, an adapter cache, a controller cache, and so on. This approach does not expose the interference that occurs when the different levels in the storage stack are all attempting to do some of the same optimizations, but cutting down on the interference is the only way we can look at the real effect of each of the optimizations. The interference is interesting but beyond the scope of the current paper. Furthermore, a well-designed system will have a level at which a particular technique dominates. For instance, for caching, the adapter cache should be bigger than the disk-drive cache so that its effect dominates. For other techniques, such as request scheduling, there is a level at which it can best be implemented. At appropriate points in the paper, we discuss such issues and how we handle them in our simulator.

Even though we simulate only a single instance of each of the optimization techniques, there are many parameters for each technique, and their combination makes for a huge design space. In order to systematically examine the effect of each technique, we pick two reasonable base configurations and perturb them in *one* dimension

at a time. The *default* parameters used in these base configurations are summarized in Figure 2. As we study each technique individually, the relevant parameters are analyzed and described in detail. As its name suggests, the resource-rich configuration is meant to represent an environment in which resources in the storage system are plentiful, as may be the case when there is a large outboard controller. The resource-poor environment is supposed to mimic a situation in which the storage system consists of only disks and low-end disk adapters.

Our simulator is written in C++ using the CSIM simulation library [30]. It is based upon a detailed model of the mechanical components of the IBM Ultrastar* 73LZX [31] family of disks that is used in disk development and that has been validated against test measurements obtained on several batches of the disk. We model the disk to a similar level of detail as in the publicly available DiskSim package [32]. However, instead of using the same seek profile for reads and writes and accounting for the difference by a constant write-settling delay, we use separate read and write seek curves to more accurately model the disk. As shown in **Figure 3**, the seek curves for this disk can be approximated by a power function for seeks of less than 5000 tracks and a linear function for longer seeks.

The IBM Ultrastar 73LZX family of 10K-rpm disks was introduced in early 2001 and consists of four members with storage capacities of 9.1, 18.3, 36.7, and 73.4 GB. The performance characteristics of each are almost identical, with the difference in capacity coming from the number of platters. The higher-capacity disk should have a longer seek time because of the increased inertia of the disk arm, but the effect is small. The average seek time is specified to be 4.9 ms, and the data rate varies from 29 MB/s at the inner edge to 57 MB/s at the outer edge. The track density for this series of disks is 27,000 tracks per inch, while the linear density is as high as 480,000 bits per inch. The tracks range in size from 160 KB to 340 KB. More details about the specifications of this family of disks can be found in [31]. To understand the effects of the evolution of disk technology, in Section 5 we scale these disk characteristics according to technology trends that we derive by analyzing the specifications of disks introduced in the last ten years.

For workloads with multiple disk volumes, we concatenate the volumes to create a single address space. In the base configurations, each workload is fitted to the smallest disk from the IBM Ultrastar 73LZX family that is bigger than the total volume size, resulting in an average storage-used-to-disk-capacity ratio of about 55%. We leave a headroom of 20% because the results presented here are part of a larger study that examines the results when up to 20% of the disk blocks are replicated and laid out in an area of the disk that is specially set aside [4]. When we

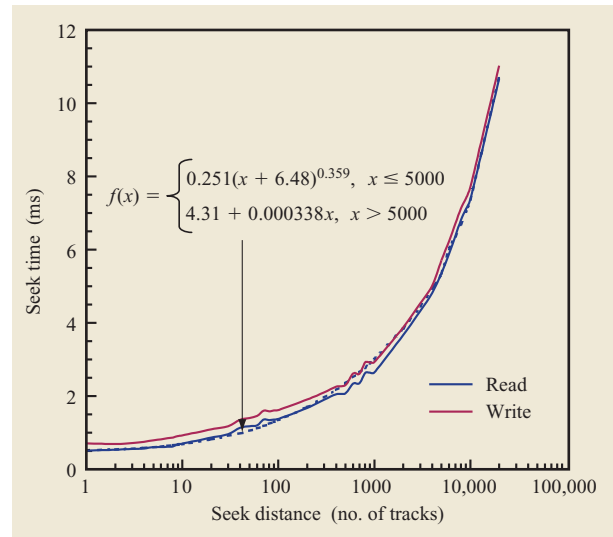


Figure 3

Seek profile for the IBM Ultrastar 73LZX family of disks.

study parallel I/O, we look at the effect of striping the data across multiple disks. Note that we have a separate read cache and write buffer so that we can adjust the size of each independently. Results in [3] show that there is not a lot of interaction between the reads and the writes.

Performance metrics

I/O performance can generally be measured at different levels in the storage hierarchy. In order to quantify the effect of a wide variety of storage optimization techniques, we measure performance from the time at which requests are issued to the storage system before they are potentially broken up by the volume manager for requests that span multiple disks. The two important metrics in I/O performance are *response time* and *throughput*. Response time includes both the time needed to service the request and the time spent waiting or queuing for service. Throughput is the maximum number of I/Os that can be handled per second by the system. Quantifying the throughput is generally difficult with trace-driven simulation because the workload, as recorded in the trace, is constant. We can try to scale or speed up the workload to determine the maximum workload the system can sustain, but this is difficult to achieve in a realistic manner.

In this paper, we estimate the throughput by considering the amount of critical resource each I/O consumes. Specifically, we consider the average amount of time the disk arm is busy per request, deeming the disk arm to be busy both when it is being moved into position to service a request and when it has to be kept in position to transfer data. We refer to this metric as the *service*

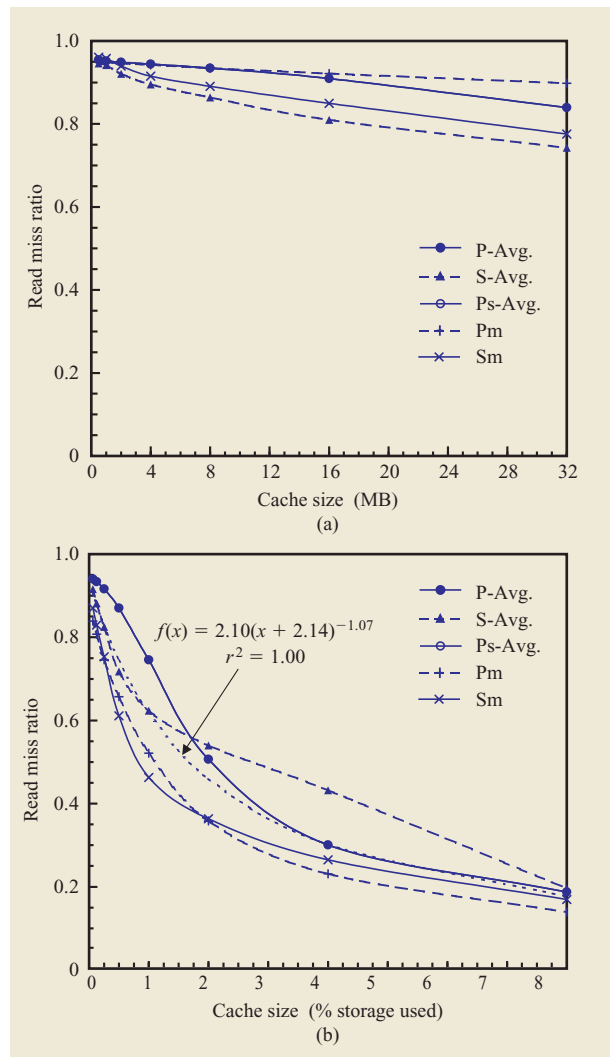


Figure 4

Effectiveness of read caching (LRU) at reducing physical reads: (a) Resource-poor environment. (b) Resource-rich environment.

time. Throughput can be approximated by taking the reciprocal of the average service time. It should be noted that there are opportunistic techniques, especially for reads (e.g., preemptible read ahead), that can be used to improve performance. The service time does not include the otherwise idle time that the opportunistic techniques exploit. This means that the reciprocal of the service time tends to be an optimistic estimate of the maximum throughput, especially in the case of a lightly loaded disk where opportunistic techniques are likely to have a bigger effect.

To gain insight into the workings of the different optimization techniques, we also examine the effective miss ratio of the read cache and the write buffer. The miss ratio is generally defined as the fraction of I/O requests

that are not satisfied by the cache or buffer or, in other words, the fraction of requests that require physical I/O. To make our results more useful for subsequent mathematical analyses and modeling by others, we fitted our data to various functional forms through nonlinear regression, which we solved by using the Levenberg-Marquardt method [33].

4. Effect of I/O optimizations

Read caching

Caching is a general technique for improving performance by temporarily holding in a faster memory those data items that are (believed to be) likely to be used. The faster memory is called the *cache*. In the context of this paper, the data items are disk blocks requested from the storage system, and the faster memory refers to dynamic random access memory (DRAM). The fraction of requests satisfied by the cache is commonly called the *hit ratio*. The fraction of requests that have to be handled by the underlying storage system is referred to as the *miss ratio*. The data items can be entered into the cache when they are demand-fetched or when it is anticipated that they are likely to be referenced soon. Caching usually refers only to the former. The latter is generally called *prefetching* and is discussed in detail in the next section. Note that to focus on the effect of caching, we disable prefetching. This is an exception to our general approach of perturbing, at any one time, only the parameters for *one* technique from their default values listed in Figure 2.

Figure 4 shows the effectiveness of read caching at reducing physical reads. Unless otherwise noted, the cache block size is 4 KB. We use the least-recently-used (LRU) replacement policy, since variations of it are commonly used throughout computer systems. Notice from Figure 4(a) that the cache is not very useful for sizes up to 32 MB. This is expected because we are looking at the physical reference stream, which has been filtered by the caching going on upstream in the host system. Today, it is common even for PC systems to have more than 100 MB of main memory, much of which can be used for file caching. Yet most disks have only 2–4 MB of cache, with some offering an 8-MB option. Our results suggest that the disk drive cache is not very effective at such sizes. It serves primarily as a buffer for prefetching.

Note that if the cache is large enough to hold all of the blocks that will be referenced again, the performance will obviously be very good. However, we will need a huge cache, because [Figure 4(b)] the miss ratio continues to improve at cache sizes that are beyond 4% of the storage used (allocated). In practice, there is a limit to the size of the cache because of addressing and packaging limitations and cost. Today, most enterprise-class outboard storage controllers, when fully loaded, have cache sizes that are in

Table 2 Performance with read caching (LRU), showing percentage of improvement over a system with almost no (512 KB) cache.

	Resource-poor environment						Resource-rich environment					
	Average read response time		Average read service time		Read miss ratio		Average read response time		Average read service time		Read miss ratio	
	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(%) ⁱ	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(%) ⁱ	(%) ⁱ
P-Avg.	6.27	2.46	4.31	2.11	0.934	2.12	5.00	22.9	3.42	22.3	0.746	22.0
S-Avg.	5.34	9.01	3.88	8.34	0.864	8.93	3.54	38.8	2.72	35.7	0.623	34.2
Ps-Avg.	6.96	2.33	4.34	2.09	0.934	2.13	5.73	20.6	3.49	21.5	0.746	22.0
Pm	6.04	2.26	4.18	1.83	0.935	1.81	3.15	49.0	2.27	46.6	0.521	45.2
Sm	5.69	6.36	4.10	6.34	0.891	7.27	2.69	55.7	1.99	54.5	0.463	51.8

ⁱ Improvement over 512-KB cache (buffer) $[(original\ value - new\ value)/(original\ value)]$.

Resource-poor environment: 8 MB per disk, least-recently-used (LRU) replacement.

Resource-rich environment: 1% of storage used, LRU replacement.

the range of 0.05–0.2% of the storage space [34–36]. In this study, in the resource-rich environment we set the cache size aggressively to 1% of the storage used and 8 MB per disk in the resource-poor environment. The cost per GB for DRAM is currently about 50 times higher than for disk storage. This means that a cache that is 1% of the storage space and does nothing but helps mask the poor performance of the disk will cost as much as half the disk storage. Though high, this level of cost is likely to be acceptable because it is about half that incurred by sites that mirror instead of parity-protect their disks. Note also that as disks become a lot bigger and PCs have at least one disk, the amount of cache needed in the PC environment to hold 1% of the data stored may be much less than the amount of cache needed to store 1% of the disk capacity.

To establish a rule of thumb relating the read miss ratio to the size of the cache, we took the average of the five plots in Figure 4(b) and fitted various functional forms to it. As shown in the figure, a good fit is obtained with a power function of the form $f(x) = a(x - b)^c$, where a , b , and c are constants. This relationship, based on the physical I/O stream, turns out to be functionally similar to that found at the logical level for large database systems [17]. However, at the logical level, the c value is about half of the -1 in our case. This means that the physical read miss ratio for our workloads improves faster with increase in the cache size than is the case at the logical level for large database systems. Such results suggest that caching can be effective at the physical level provided that the cache is large enough.

In Table 2, we summarize the effectiveness of read caching at improving performance. Throughout this paper, we define improvement as $(original\ value - new\ value)/(original\ value)$ if a smaller value is better, and $(new\ value - original\ value)/(original\ value)$ otherwise. Note that some amount of cache memory is needed as a speed-matching

buffer between the disk media and the disk interface with the host. In other words, we need to configure our simulator with some small but non-zero amount of cache memory. Therefore, the improvement reported in Table 2 is relative to the performance with a small (512-KB) cache. As discussed earlier, in the resource-poor environment, caching is relatively ineffective, achieving only about 6% improvement in average read response time and about 4% in average read service time. In the resource-rich environment, the improvement ranges from about 20% for the base PC workloads to more than 50% for the merged workloads.

Note that these numbers are for a cache block size of 4 KB. For historical reasons, the sector, or smallest addressable unit in most storage systems today, is 512 B. Managing the cache at such a small granularity is very inefficient because of the large data structures needed to manage them and because most I/O transfers are much larger than 512 B. To reduce the management overhead, a larger cache block can be used together with valid bits to indicate whether each sector within the block is present in the cache. This is similar to the sector cache approach in processor cache. In [5], we evaluate the impact of using a large cache block on the effectiveness of the cache and find that a cache block size of 4 KB is reasonable for our workloads. We use this block size for the rest of this paper. Note that the cache block size is the unit of cache management. It is independent of the fetch or transfer size, which we analyze in the following section.

Prefetching

Prefetching is the technique of predicting blocks that are likely to be used in the future and fetching them before they are actually needed. The overall effectiveness of prefetching at improving performance hinges on 1) the accuracy of the prediction, 2) the amount of extra

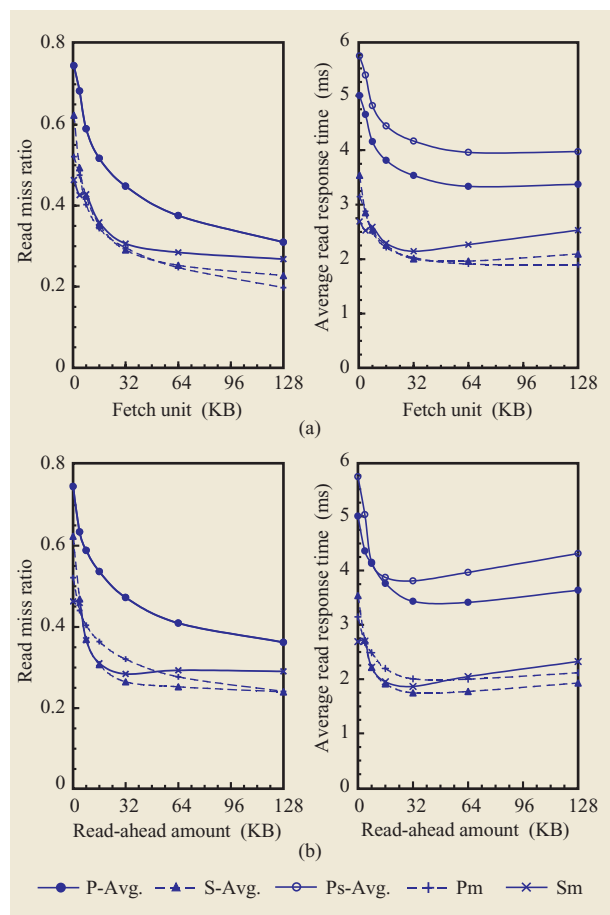


Figure 5

Effect of (a) large fetch unit and (b) read ahead on read miss ratio and response time in a resource-rich environment.

resource (memory use, disk and data-path busy time, etc.) that is consumed by the prefetch, and 3) the timeliness of the prefetch, i.e., whether the prefetch is completed before the blocks are actually needed.

The prediction is usually based on past access patterns [9, 17], although in certain situations, system-generated plans [37, 38], user-disclosed hints [19], and guidance from speculative execution [39] may be available to help with the prediction. In general, the prediction is not perfect, so that prefetching consumes more resource than demand fetching. Specifically, it congests the I/O system and may pollute memory with unused pages. Memory pollution is the loading of pages that are not referenced and the displacement of pages that will be referenced. For many storage devices, particularly disk drives, however, a large sequential access is much more efficient than multiple small random accesses. For such devices, prefetching of sequential pages has the potential to increase I/O

efficiency by transforming several small block I/Os into one large block I/O that can be more efficiently handled by the I/O device. Moreover, most workloads exhibit sequentiality in their I/O access patterns, so that sequential prefetch, especially if performed on a cache miss, scores well on all three criteria (prediction accuracy, cost, and timeliness) listed above. Therefore, practically all storage systems today implement some form of sequential prefetch on cache miss. We focus on such a prefetch in this paper. By default, we assume that data is prefetched into the cache and managed as if it were demand-fetched. The prefetched data could instead be placed in a separate buffer or be handled in the cache differently than demand-fetched data (e.g., be evicted earlier). The interested reader is referred to [17] for an evaluation of such alternatives.

Several researchers have also proposed schemes for automatically matching up access patterns with previously observed contexts, and then prefetching according to the previously recorded reference patterns (e.g., [8]). Such prefetching schemes should score well in the accuracy criteria, but because they incur additional random I/Os (which are slow and inefficient) to perform the prefetch, they may not do as well in the cost and timeliness criteria. We look at an alternative to context-based prefetch in [4].

Large fetch unit

Sequential prefetch can be achieved relatively easily by using a *large fetch unit*, or transfer size. For example, if the fetch unit is 64 sectors or blocks, a read request for blocks 60–68 causes blocks 0–127 to be fetched. Thus, a large fetch unit, effectively a large block size, generally prefetches blocks both preceding and following the target blocks. Because the preceding blocks are fetched before the target blocks to avoid an extra disk revolution, there is a response-time penalty for having a large fetch unit. Furthermore, the entire transfer must be complete before an I/O interrupt is received, although in an alternate design the fetch could be broken into one that terminated at the target blocks while a second one obtained the remaining blocks.

In **Figure 5(a)**, we plot the effect of having a large fetch unit on the read miss ratio and the average read response time for the resource-rich environment. The corresponding plots for the resource-poor environment are similar and can be found in [5]. Observe that a large fetch unit significantly reduces the read miss ratio, with most of the effect occurring at fetch units that are smaller than about 64 KB. As the fetch unit is increased beyond 64 KB, the average read response time starts to rise because the penalty of having to fetch the blocks preceding and following the target blocks inline begins to outweigh the benefit of the relatively small marginal improvement in read miss ratio. Previously, a one-track fetch unit was recommended [6], but since then physical track sizes have grown from the 10-KB

Table 3 Performance improvement with prefetching, showing percentage of improvement over a system that does not prefetch.

	Average read response time						Average read service time						Read miss ratio					
	LFU ⁱ		RA ⁱ		CSP ⁱ		LFU ⁱ		RA ⁱ		CSP ⁱ		LFU ⁱ		RA ⁱ		CSP ⁱ	
	(ms)	(%) ⁱⁱ	(ms)	(%) ⁱⁱ	(ms)	(%) ⁱⁱ	(ms)	(%) ⁱⁱ	(ms)	(%) ⁱⁱ	(ms)	(%) ⁱⁱ	(%) ⁱⁱ	(%) ⁱⁱ	(%) ⁱⁱ	(%) ⁱⁱ	(%) ⁱⁱ	(%) ⁱⁱ
Resource-poor environment																		
P-Avg.	4.29	32.1	4.25	32.4	4.14	34.3	2.74	36.2	2.99	30.4	2.93	31.9	0.484	48.2	0.587	37.2	0.518	44.6
S-Avg.	3.29	39.3	3.03	44.5	2.75	49.6	2.27	41.3	2.26	41.9	2.08	46.5	0.393	54.4	0.427	50.6	0.383	55.6
Ps-Avg.	4.92	29.8	4.64	33.4	4.65	33.4	2.78	35.8	2.84	34.4	2.81	35.0	0.484	48.2	0.587	37.2	0.518	44.6
Pm	4.10	32.1	3.98	34.1	3.89	35.6	2.74	34.4	2.94	29.5	2.91	30.3	0.495	47.1	0.596	36.2	0.533	43.0
Sm	4.23	25.7	3.79	33.4	3.61	36.6	3.13	23.6	3.07	25.3	2.93	28.6	0.505	43.3	0.551	38.1	0.523	41.3
Resource-rich environment																		
P-Avg.	3.33	33.8	3.43	31.5	3.33	33.5	2.12	37.8	2.40	29.5	2.35	30.7	0.375	49.4	0.473	36.4	0.415	44.0
S-Avg.	1.96	39.0	1.75	47.7	1.52	53.7	1.41	37.9	1.34	43.7	1.18	49.6	0.253	53.5	0.265	52.9	0.223	59.3
Ps-Avg.	3.96	31.2	3.81	33.4	3.82	33.3	2.16	37.5	2.28	34.1	2.26	34.4	0.375	49.4	0.472	36.5	0.414	44.1
Pm	1.91	39.3	2.01	36.3	1.94	38.3	1.33	41.2	1.56	31.3	1.54	32.3	0.247	52.6	0.321	38.5	0.280	46.3
Sm	2.27	15.7	1.87	30.7	1.72	36.1	1.72	13.7	1.53	23.2	1.41	29.1	0.285	38.6	0.284	38.6	0.260	44.0

ⁱ LFU: Large fetch unit (64 KB); RA: Read ahead (32 KB); CSP: conditional sequential prefetch (16-KB segments for PC workloads, 8-KB segments for server workloads, prefetch trigger of 1, prefetch factor of 2).

ⁱⁱ Improvement over no prefetch $[(original\ value - new\ value)/(original\ value)]$.

range to about 512 KB today. However, the ability of workloads to use larger fetch units effectively has not kept pace. For all of our workloads, a relatively small fetch unit of 64 KB, or 1/8 of a track, works well.

Read ahead

In *read ahead*, after the system has fetched the blocks needed to satisfy a read request, it continues to read the blocks following; i.e., it reads ahead of the current request, hence its name. We consider the read request to be completed once all of the requested blocks have been fetched. This typically means that two start I/Os are issued—one for the requested blocks and another to read ahead and prefetch data. In **Figure 5(b)**, we explore the performance effect of reading ahead by various amounts. Observe from the figure that a read ahead of 32 KB performs well for all of our workloads. Beyond 32 KB, the read response time begins to rise slightly for some of the workloads because the read ahead is holding up subsequent demand requests, and the marginal improvement in read-miss ratio at such large read-ahead amounts is not enough to overcome the effect of this delay. Later in this section, we look at preempting the read ahead whenever a demand request arrives.

In **Table 3**, we summarize the effectiveness of the different prefetching schemes at improving performance over that of a non-prefetching system. Observe that a large fetch unit tends to reduce the read miss ratio more than read ahead does. It also has a slight advantage in read service time for the PC workloads, because the PC workloads tend to exhibit spatial locality and not just sequentiality.

In other words, not just the blocks that are following, but those that are near blocks that have been recently referenced, are likely to be accessed in the near future. Thus, a large fetch unit, by causing the blocks around the requested data to be prefetched, can achieve a higher hit ratio. However, because the use of a large fetch unit results in fetching the surrounding blocks before returning from servicing a request, it performs worse than read ahead in terms of response time, especially for the server workloads.

Conditional sequential prefetch

To reduce resource wastage from unnecessary prefetch, sequential prefetch can be initiated only when the access pattern is likely to be sequential. Generally, the amount of resources committed to prefetching should increase with the likelihood that the prediction is correct. For instance, previous studies [9, 17] have shown the benefit of determining the prefetch amount by conditioning on the length of the run or sequential pattern observed thus far. We refer to such schemes as *conditional sequential prefetch*. To condition on the run length, we need to be able to discover the sequential runs in the reference stream. This is generally difficult because of the complex interleaving of references from different processes. In this paper, we use a general sequential detection scheme patterned after that proposed in [17].

The sequential detector keeps track of references at the granularity of multiple sectors or blocks, a unit we refer to as the *segment*. A segment is considered to be referenced if any page within that segment is referenced. By detecting

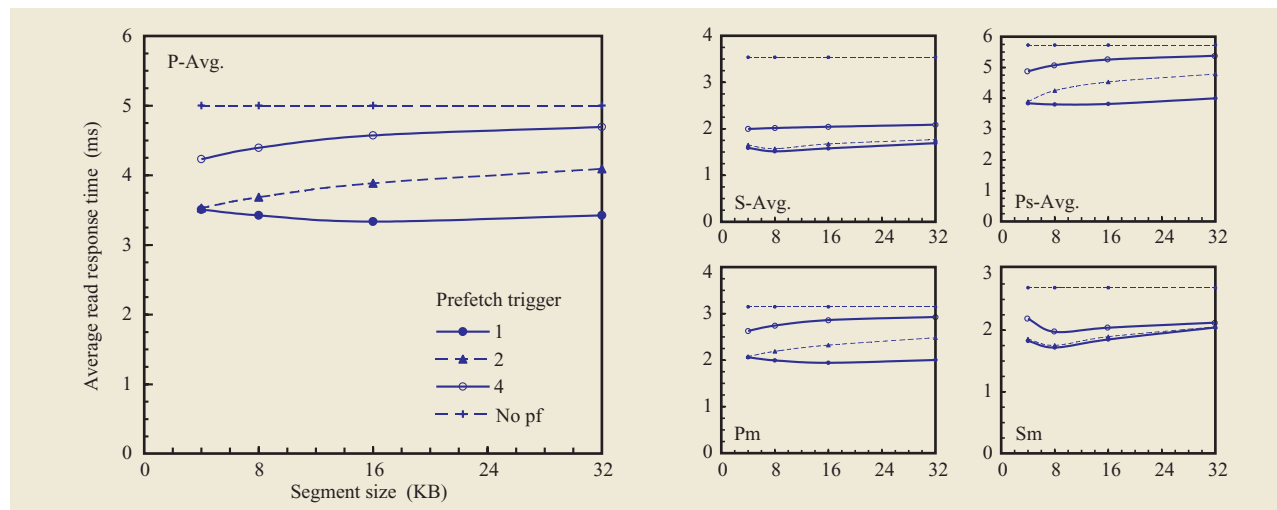


Figure 6

Average read response time with conditional sequential prefetch in a resource-rich environment.

sequentiality in segment references, we can very effectively capture pseudosequential reference patterns. The sequential detector maintains an LRU-organized list of segments. Each entry in the segment directory has a sequential run counter that tracks the length of the run ending at that segment. On a read, if the corresponding segment is not already in the segment directory, we insert it. The run counter value of the new segment entry is set to 1 if the preceding segment is not in the directory and to $1 + \text{run counter value}$ of the preceding segment otherwise. In the latter case, we remove the entry corresponding to the preceding segment. Note that the segment directory tracks sequential patterns in the actual reference stream. It is therefore updated only when read requests are encountered, not when blocks are prefetched. On a read miss, if the run counter for the segment exceeds a threshold known as the *prefetch trigger*, we initiate sequential prefetch. In this paper, the prefetch amount is set to $2 \times \text{run counter value} \times \text{segment size}$, subject to a maximum of 256 KB. The size of the segment directory governs the number of potential sequential or pseudo-sequential streams that can be tracked by the sequential detector. We use a generous 64 entries for all of our simulations.

In **Figure 6**, we explore the performance sensitivity to the segment size and the prefetch trigger. As we would expect, lower settings for the prefetch trigger perform better because the cost of fetching additional blocks once the disk head is properly positioned is small compared to the cost of a random I/O that might have to be performed later if the blocks are not prefetched. For all of the

workloads, the best performance is obtained with a prefetch trigger of 1, meaning that prefetch is triggered on every cache miss. A segment size of 16 KB works well for the PC workloads. For the server workloads, the optimal segment size is 8 KB.

In a similar fashion, we can additionally prefetch preceding blocks when a backward sequential pattern is detected. To avoid having to wait a disk revolution for the preceding blocks to appear under the disk head, the preceding blocks are fetched before the requested blocks. Except for a slight performance improvement in some of the PC workloads, such backward conditional sequential prefetch turns out not to be very useful [5].

In Table 3, we compare the performance of conditional sequential prefetch with that of large fetch unit and read ahead. The three schemes achieve roughly the same average read response time for the PC workloads, reducing it by more than 30%. For the server workloads, conditional sequential prefetch is clearly superior, improving the average read response time by 36–54%. As for read service time, the PC workloads are improved by 30–40%, with large fetch unit having an edge. For the server workloads, conditional sequential prefetch again reigns supreme, with improvement of 29–50%. In the resource-poor environment, about 40–60% of the reads remain after caching and prefetching. In the resource-rich environment, about 25–45% remain.

Opportunistic prefetch

Another way to reduce the potential negative impact of prefetch is to perform the prefetch using only resources

that would otherwise be idle or wasted. We refer to such an approach as *opportunistic prefetch*. In general, opportunistic prefetch can best be performed close to the physical device, where detailed information is available about the critical physical resources. Because a disk access costs much more than a semiconductor memory access, the cost of accessing prefetched data should be largely independent of the layer in the storage stack into which the data is prefetched. However, data prefetched into the disk drive cache tends to be evicted sooner, sometimes even before it is used, because the disk drive cache is typically smaller than the adapter and outboard controller cache. To model this effect, we enter opportunistically prefetched data into an 8-MB (LRU) prefetch buffer instead of the large cache in the resource-rich environment. The prefetch buffer turns out to significantly reduce pollution of the large cache.

The simplest form of opportunistic prefetch is to read ahead up to a maximum amount or until a demand request arrives, at which point the read ahead is terminated. This is known as *preemptible read ahead*. Read ahead by the disk is usually preemptible. At the adapter/controller level, it is generally difficult to preempt a request that has been issued to the disk, but the request can be broken up into smaller subrequests to enable preemption between them (e.g., [40]). By terminating the read ahead as soon as another demand request arrives, preemptible read ahead avoids holding up subsequent requests. Thus, its performance does not degrade as the maximum read-ahead amount is increased (**Figure 7**). However, preemptible read ahead tends not to perform as well as non-preemptible read ahead, especially for the speeded-up workloads, because it may be preempted before it can perform any effective prefetch. Such results suggest a hybrid approach of performing preemptible read ahead in addition to the non-opportunistic prefetching schemes discussed above. In such an approach, we would always perform some amount of prefetch (non-opportunistic) and, if idle resources were available, we would prefetch more (opportunistic). We find that with the hybrid approach, an opportunistic prefetch limit of 128 KB works well in almost all of the cases [5]. This is the value that we assume for the rest of the paper. An opportunistic prefetch limit of 128 KB means that blocks are opportunistically prefetched only until a total of 128 KB of data has been prefetched.

Table 4 summarizes the impact of performing preemptible read ahead in addition to the various non-opportunistic prefetching schemes in the resource-rich environment. The corresponding table for the resource-poor environment can be found in [5]. We find that in the resource-poor environment, preemptible read ahead improves average read response time by about 5% for large fetch unit and read ahead. The improvement is

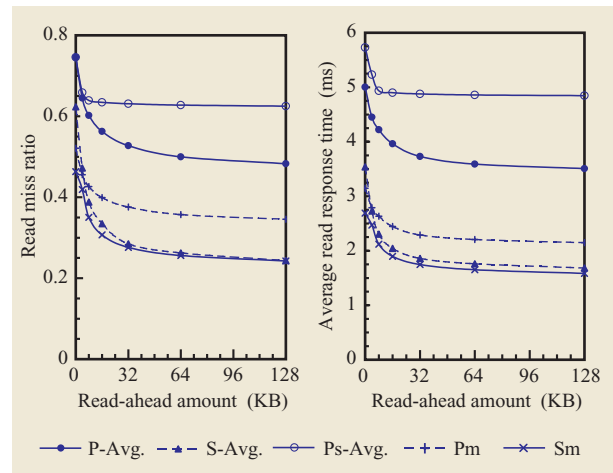


Figure 7

Effect of preemptible read ahead on read miss ratio and response time in a resource-rich environment.

smaller for conditional sequential prefetch because conditional sequential prefetch already uses resources carefully by determining the amount to prefetch on the basis of the potential usefulness of the prefetch. In the resource-rich environment, preemptible read ahead has a bigger effect, especially for the server workloads, which are improved by about 15–20%.

Another opportunistic prefetching technique is to start reading once the disk head is positioned over the correct track. Such a scheme is known as *read-any-free-blocks*, or *zero latency read*. Basically, it uses the rotational delay to perform some prefetching free of cost. Such a scheme may prefetch some blocks that precede the requested data and/or some blocks that come after, depending on the time at which the head is properly positioned. For example, if the head is positioned to read just after the requested data has rotated under, read-any-free-blocks fetches the succeeding blocks until the end of the track and then continues reading the blocks at the beginning of the track. As shown in Table 4, read-any-free-blocks is quite effective at improving performance. Our results indicate that in the resource-poor environment, read-any-free-blocks with preemptible read ahead is able to reduce the average read response time with read ahead by about 20% for the PC workloads and by more than 10% for the server workloads. In the resource-rich environment, the additional improvement is more than 20% for all of the workloads. Again, conditional sequential prefetch is improved less because it performs large prefetches only when they are warranted. As for large fetch unit, it is improved the least by read-any-free-blocks because it already prefetches some of the preceding blocks.

Table 4 Additional effect of opportunistic prefetch in a resource-rich environment, showing percentage of improvement over a system that performs only non-opportunistic prefetch.

	<i>Average read response time</i>						<i>Average read service time</i>						<i>Read miss ratio</i>					
	<i>LFUⁱ</i>		<i>RAⁱ</i>		<i>CSPⁱ</i>		<i>LFUⁱ</i>		<i>RAⁱ</i>		<i>CSPⁱ</i>		<i>LFUⁱ</i>		<i>RAⁱ</i>		<i>CSPⁱ</i>	
	(ms)	(%) ⁱⁱ	(ms)	(%) ⁱⁱ	(ms)	(%) ⁱⁱ	(ms)	(%) ⁱⁱ	(ms)	(%) ⁱⁱ	(ms)	(%) ⁱⁱ	(%) ⁱⁱ	(%) ⁱⁱ	(%) ⁱⁱ	(%) ⁱⁱ	(%) ⁱⁱ	(%) ⁱⁱ
Preemptible read ahead																		
P-Avg.	2.97	11.9	3.13	10.2	3.15	6.84	1.81	14.9	2.10	13.1	2.15	9.25	0.336	10.8	0.411	13.7	0.381	8.95
S-Avg.	1.71	15.2	1.45	18.8	1.32	13.5	1.20	17.7	1.04	22.8	0.98	16.4	0.212	19.1	0.204	23.7	0.186	16.1
Ps-Avg.	3.76	5.40	3.65	4.99	3.69	4.49	1.99	7.79	2.13	7.24	2.13	6.43	0.371	1.15	0.437	8.07	0.391	6.28
Pm	1.67	12.3	1.96	2.46	1.98	-2.15	1.14	14.6	1.45	6.99	1.50	2.25	0.223	9.90	0.296	7.75	0.275	1.60
Sm	2.05	9.8	1.44	22.8	1.38	19.6	1.56	9.47	1.14	25.4	1.10	22.1	0.257	9.79	0.212	25.3	0.205	21.2
+ Read-any-free-blocks ⁱⁱⁱ																		
P-Avg.	2.76	18.3	2.57	26.7	2.66	22.2	1.68	20.8	1.71	29.6	1.79	25.0	0.310	17.8	0.332	30.5	0.313	25.6
S-Avg.	1.65	18.7	1.32	27.4	1.20	22.6	1.16	20.8	0.947	31.3	0.886	25.7	0.204	22.6	0.182	32.8	0.167	26.0
Ps-Avg.	3.47	13.1	3.03	22.1	3.15	19.3	1.81	16.3	1.69	26.7	1.75	23.8	0.336	10.7	0.348	27.0	0.319	24.0
Pm	1.57	17.8	1.59	20.9	1.65	15.0	1.07	19.9	1.17	25.3	1.24	19.4	0.207	16.0	0.238	25.8	0.226	19.4
Sm	1.99	12.4	1.44	22.8	1.38	19.9	1.52	11.8	1.15	24.7	1.10	22.2	0.249	12.6	0.212	25.3	0.204	21.3
+ Just-in-time seek ^{iv}																		
P-Avg.	2.71	19.9	2.66	24.3	2.80	18.0	1.50	29.7	1.52	37.4	1.65	30.7	0.287	24.1	0.318	33.6	0.308	26.8
S-Avg.	1.63	20.1	1.29	29.5	1.21	22.1	1.04	29.7	0.800	42.6	0.769	36.0	0.198	24.7	0.171	37.5	0.162	28.5
Ps-Avg.	3.38	15.5	3.20	17.8	3.37	13.5	1.46	32.9	1.49	35.4	1.64	28.5	0.303	19.9	0.335	30.0	0.317	24.5
Pm	1.54	19.3	1.65	17.8	1.76	9.31	0.927	30.5	1.01	35.1	1.13	26.4	0.190	22.9	0.229	28.7	0.223	20.1
Sm	1.97	13.0	1.42	24.1	1.33	22.4	1.38	20.0	1.01	34.4	0.94	33.3	0.242	14.9	0.204	28.1	0.194	25.1

ⁱ LFU: Large fetch unit (64 KB); RA: Read ahead (32 KB); CSP: Conditional sequential prefetch (16-KB segments for PC workloads, 8-KB segments for server workloads, prefetch trigger of 1, prefetch factor of 2).

ⁱⁱ Improvement over non-opportunistic prefetch $[(original\ value - new\ value)/(original\ value)]$.

ⁱⁱⁱ Preemptible read ahead + read-any-free-blocks.

^{iv} Preemptible read ahead + read-any-free-blocks + just-in-time seek.

The dual technique of read-any-free-blocks is *just-in-time seek*, or *delayed preemption* [41]. The idea here is that when a request arrives while the disk is performing preemptible read ahead, the disk should continue with the read ahead and move the head to service the incoming request only in time for the head to be positioned over the correct track before the requested data rotates under. Basically, this allows the disk to prefetch more of the succeeding blocks. As shown in Table 4, the additional use of just-in-time seek improves performance for large fetch unit slightly over performing only read-any-free-blocks and preemptible read ahead. For read ahead and conditional sequential prefetch, just-in-time seek offers a marginal performance improvement in addition to that from read-any-free-blocks and preemptible read ahead for the server workloads, but loses out for the PC workloads.

During the rotational delay, the disk can also be used to perform I/Os that are tagged as lower-priority. This technique is called *freeblock scheduling* [42] and is meant to allow tasks such as disk scrubbing and data mining to be performed in the background with no impact on the foreground work. For instance, if the next block to be

read is halfway around the track, the disk head could be positioned to service background requests “free of cost” as long as it could be moved back in time to read the block as it rotates under the head. However, given that read-any-free-blocks and just-in-time seek are effective at improving performance, such background I/Os may not be totally free for our workloads.

In general, in both the resource-poor and resource-rich environments, the best performance is obtained for the PC workloads when preemptible read ahead and read-any-free-blocks are performed in addition to simple read ahead. Specifically, this means starting to read once the disk head is positioned over the correct track, and reading beyond the requested data by 32 KB and, if there are no incoming requests, by up to 128 KB. The average read response time in this case is improved by almost 50% over that of a system that does not prefetch (Table 5). For the server workloads, performance improvement of 42–54% in the resource-poor environment and up to 65% in the resource-rich environment is achieved when conditional sequential prefetch is supplemented by preemptible read ahead and read-any-free-blocks.

Table 5 Overall effect of performing preemptible read ahead and read-any-free-blocks in addition to non-opportunistic prefetch, showing percentage of improvement over a system that does not prefetch.

	Resource-poor environment									Resource-rich environment								
	Average read response time			Average read service time			Read miss ratio			Average read response time			Average read service time			Read miss ratio		
	LFU ⁱ	RA ⁱ	CSP ⁱ	LFU ⁱ	RA ⁱ	CSP ⁱ	LFU ⁱ	RA ⁱ	CSP ⁱ	LFU ⁱ	RA ⁱ	CSP ⁱ	LFU ⁱ	RA ⁱ	CSP ⁱ	LFU ⁱ	RA ⁱ	CSP ⁱ
P-Avg.	39.5	47.3	46.1	44.9	48.3	46.3	53.7	53.9	56.8	45.7	49.7	48.2	50.6	50.4	48.1	58.3	55.8	58.4
S-Avg.	44.3	51.7	54.2	46.8	51.1	52.9	59.4	59.8	61.7	48.7	61.8	64.6	47.9	61.0	63.2	61.7	68.0	70.2
Ps-Avg.	35.3	45.3	43.5	42.6	49.5	48.0	50.8	51.8	55.9	40.0	48.0	46.1	47.5	51.7	50.0	54.8	53.6	57.5
Pm	38.8	48.0	46.8	42.1	46.7	44.5	51.7	52.1	54.8	50.1	49.6	47.6	52.9	48.6	45.5	60.2	54.4	56.7
Sm	30.6	40.8	42.1	28.7	34.8	36.2	47.5	47.5	48.4	26.2	46.5	48.8	23.9	42.2	44.8	46.3	54.2	55.9

ⁱ LFU: Large fetch unit (64 KB); RA: Read ahead (32 KB); CSP: Conditional sequential prefetch (16-KB segments for PC workloads, 8-KB segments for server workloads, prefetch trigger of 1, prefetch factor of 2).

Sensitivity to cache size

In Figure 8, we analyze performance sensitivity to cache size when data is prefetched into the cache and managed as if it were demand-fetched. We use the default parameters shown in Figure 2, meaning that in the resource-poor environment [Figure 8(a)], we read ahead by at least 32 KB on every cache miss and up to 128 KB if there are no incoming requests. We also perform read-any-free-blocks. In the resource-rich environment [Figure 8(b)], we perform conditional sequential prefetch, together with preemptible read ahead and read-any-free-blocks.

Observe that with prefetching, more than 50% of the reads can be satisfied by a 4-MB cache. Increasing the cache size beyond 4 MB to 32 MB achieves only diminishing returns. Such results suggest that disk drive caches in the megabyte range are sufficient. On the other hand, for very large caches, the miss ratio continues to improve as the cache size is increased beyond 4% of the storage used. As discussed earlier, most enterprise-class outboard storage controllers today, when fully loaded, have a front-end to back-end (cache size to storage space) ratio between 0.05% and 0.2% [34–36]. Our results suggest that increasing the cache size for these systems is likely to continue to improve performance, although whether such large cache sizes are cost-effective is another issue. Note also that the desirable amount of cache may not scale linearly with the size of the system.

Write buffering

The term *write buffering* refers to the technique of temporarily holding written data in fast memory (typically semiconductor) before destaging the data to permanent storage. A write operation can be reported as completed once its data has been accepted into the buffer. Because writes tend to come in bursts [3], the write buffer helps to better regulate the flow of data to permanent storage. To prevent any loss of data if the system fails before the

buffered data is written to permanent storage, the write buffer is typically implemented with some form of non-volatile storage (NVS). In some environments, (e.g., UNIX file system, PC disks), a less expensive approach of periodically (usually every 30 seconds) flushing the buffer contents to disk is considered sufficient. By delaying the time at which the written data is destaged to permanent storage, write buffering makes it possible to combine multiple writes to the same location into a single physical write, thereby reducing the number of physical writes that have to be performed by the system. It may also increase the efficiency of writes by allowing multiple consecutive writes to be merged into a single big-block I/O. In addition, more sophisticated techniques can be used to schedule the writes to take advantage of the characteristics and the state of the storage devices.

In short, the write buffer achieves three main effects. First, it hides the latency of writes by deferring them to some later time. Second, it reduces the number of physical writes, and third, it enables the remaining physical writes to be performed efficiently. In this paper, we evaluate write buffering using a general framework that is flexible enough for us to examine the three effects of write buffering separately. In this framework, a background destage process is initiated whenever the *fraction* of “dirty” (or modified) blocks in the write buffer exceeds a high-limit threshold, *highMark*, and is suspended once the *fraction* of dirty blocks in the buffer drops below a low-limit threshold, *lowMark*. By appropriately setting *highMark*, we can ensure that buffer space is available to absorb the incoming writes. To avoid impact on the read response time, destage requests are not serviced unless there are no pending read requests or the write buffer is full. In the latter case, destage requests are serviced at the same priority as the reads. Analysis in [3] shows that the I/O workload is bursty, which implies that the storage

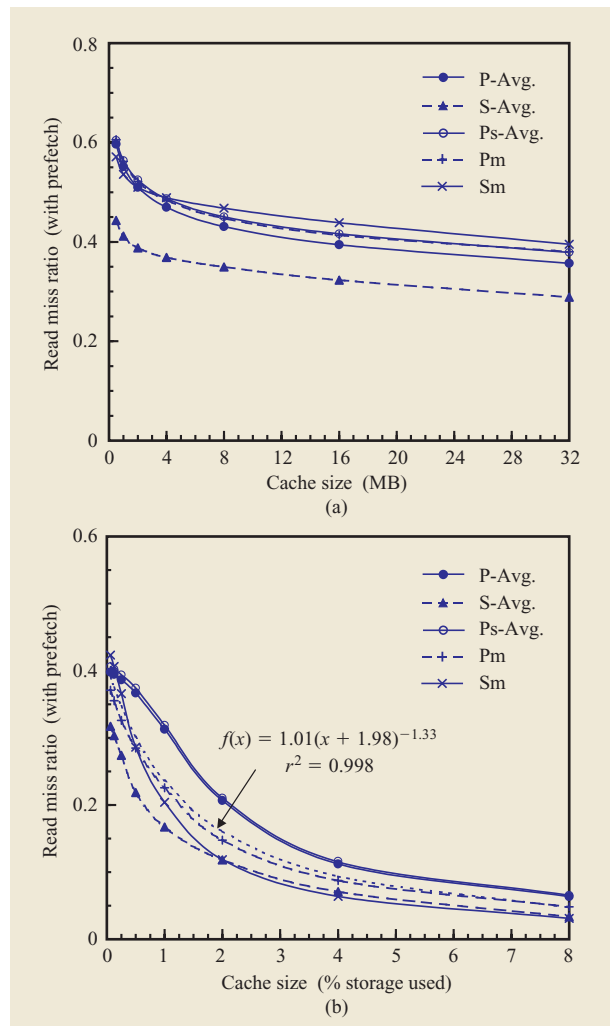


Figure 8

Sensitivity to cache size when data is prefetched into the cache and managed like demand-fetched data: (a) Resource-poor environment. (b) Resource-rich environment.

system has idle periods during which the destage requests can be handled.

To reduce the number of physical writes, we use the least-recently-written (LRW) policy to decide which blocks to destage [17]. The LRW policy is similar to the LRU policy for read caching and is so named because it selects the block that was least recently written for destage. To examine the effect of limiting the age of dirty data in the buffer, we also destage a block when its age exceeds the maximum allowed. Destage policies have been studied in some detail recently, but the focus has been on selecting blocks to destage on the basis of the efficiency with which buffer space can be reclaimed. For instance, in [10] the track with the most dirty blocks is selected for destage.

In [11] the blocks that can be written most quickly are selected. But a destage policy that strives to quickly reclaim buffer space may not be effective if the blocks that are destaged will be dirtied again in the near future. Moreover, with the layered approach of building systems, estimates of the cost of destaging operations may not be available to the destage process. For example, the adapter or outboard controller housing the write buffer typically has no accurate knowledge of the state and geometry of the underlying disks.

The approach we take is to first focus on reducing the number of physical writes by destaging blocks that are less likely to be rewritten and to then perform the remaining writes efficiently. To achieve the latter, whenever a destage request is issued, we include in the same request contiguous blocks that are also dirty. The resulting disk write may span tracks, but it is a large sequential write which can be efficiently handled by the disk. Also, we allow as many outstanding destage requests (contiguous blocks) as the maximum queue depth seen by the host, and once the destage process is initiated, it stops only when the *fraction* of dirty blocks in the buffer drops below a low-limit threshold, *lowMark*. By setting *lowMark* to be significantly lower than *highMark*, we achieve a hysteresis effect which prevents the destage process from being constantly triggered whenever new blocks become dirty. Therefore, instead of a continual trickle of destage requests, we periodically receive a burst of destage requests that can be effectively scheduled.

Absorbing write bursts

To investigate the amount of buffer space needed to absorb the write bursts, we set both the *highMark* and *lowMark* to zero. This ensures that dirty blocks are destaged at the earliest opportunity to make room for buffering the incoming writes. In Figure 9, we plot the average write response time as a function of the buffer size. In order to generalize our results across the different workloads, we also normalize the buffer size to the amount of storage used.

When the write buffer is not large enough to absorb the write bursts, some of the writes will stall until buffer space is reclaimed by destaging some of the dirty blocks. When the buffer is large enough, all of the write requests can be completed without stalling. Notice that for all of the workloads, a write buffer of 4–8 MB or 0.05–0.1% of the storage used is sufficient to effectively absorb the write bursts. In fact, for the PC workloads, a small write buffer of about 1 MB, or 0.01% of the storage used, is able to hide most of the write latency. As in the case of the read cache, we investigated the effect of different buffer block sizes, or units of buffer management, and again found that 4 KB is reasonable for our workloads [5].

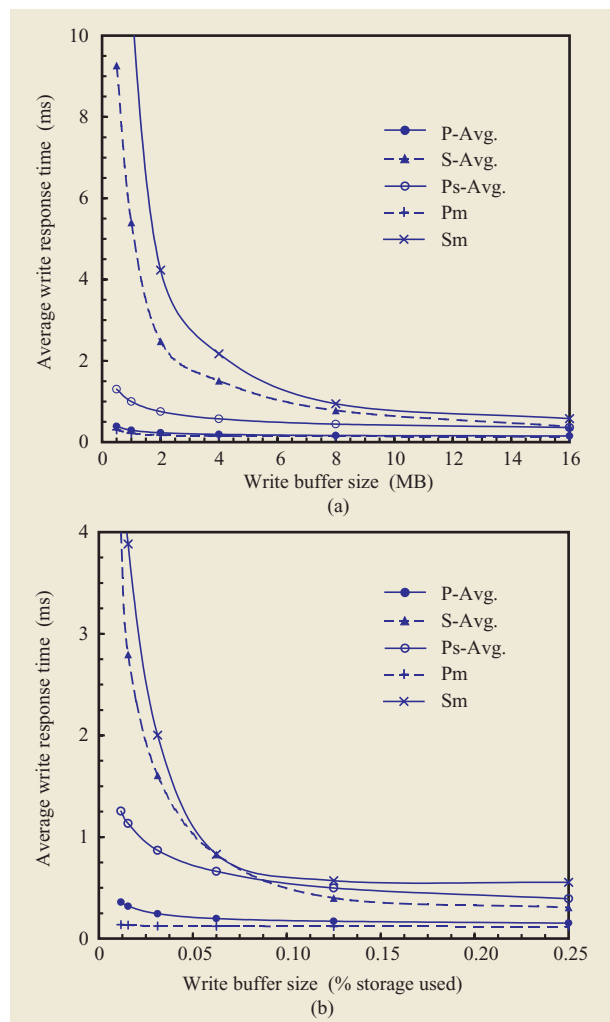


Figure 9

Improvement in average write response time from absorbing write bursts (dirty blocks are eagerly destaged): (a) Resource-poor environment. (b) Resource-rich environment.

Eliminating repeated writes

As mentioned earlier, when data is updated again before it is destaged, the second update effectively cancels out the previous update, thereby reducing the number of physical writes to the storage system. In this section, we focus on the amount of buffer space needed to effectively allow repeated writes to the same location to be canceled. We set the *highMark* and *lowMark* to 1 to maximize the probability that a write will “hit” in the write buffer.

In **Figure 10**, we plot the write miss ratio as a function of the buffer size. We define the write miss ratio as the fraction of write requests that causes one or more buffer blocks to become dirty. Thus, the write miss ratio is

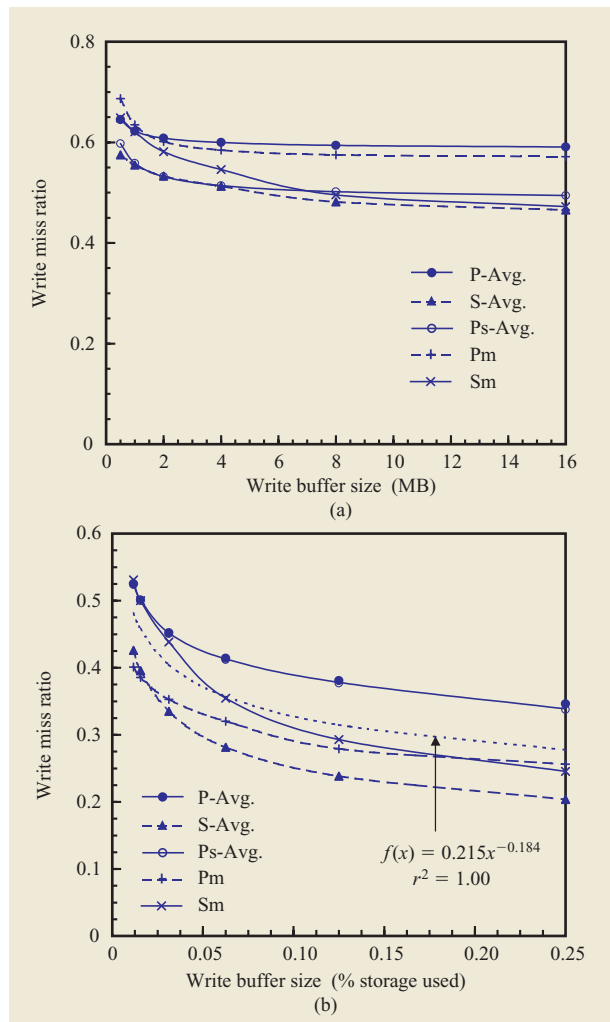


Figure 10

Effectiveness of write buffering (LRW) at reducing physical writes (dirty blocks are lazily destaged): (a) Resource-poor environment. (b) Resource-rich environment.

essentially the fraction of write requests that are not canceled. As in the case of the read cache, we took the arithmetic mean of the plots for the five different classes of workloads and fitted various functional forms to it. As shown in Figure 10(b), a power function of the form $f(x) = a(x - b)^c$ is again a good fit. However, the magnitude of the exponent c at about 0.2 is significantly lower than it is for reads, meaning that for large buffer sizes, the write miss ratio decreases much more slowly with a buffer size increase than is the case for reads. Such a behavior of the physical I/O stream turns out to parallel what has been observed at the logical level for large database systems in which the sizes of the read and write exponents are about 0.5 and 0.25, respectively [17].

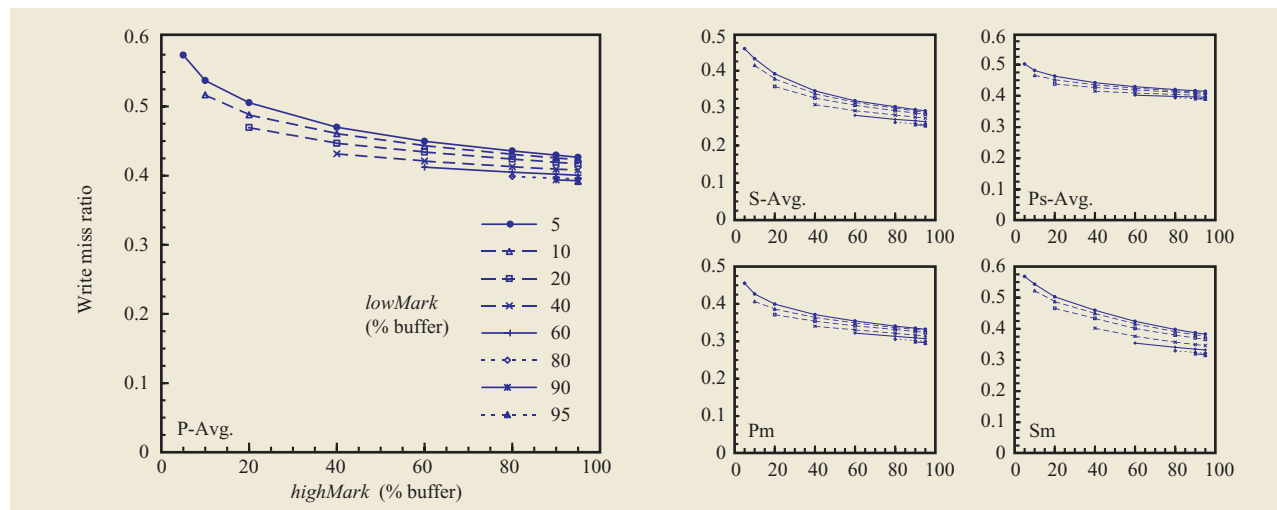


Figure 11

Effect of *lowMark* and *highMark* threshold values on write miss ratio in a resource-rich environment.

Observe from Figure 10(b) that for all of the workloads, 60–75% of the writes are eliminated at buffer sizes that are less than 0.1% of the storage used. In the resource-poor environment [Figure 10(a)], we limit the age of dirty blocks in the buffer to be less than 30 seconds. There is, therefore, less write cancellation (about 40–50% less), and most of it occurs at very small buffer sizes (about 2 MB). In general, when there is concern about losing buffered data, limits have to be placed on the maximum age of the buffered data. In [5], we analyze the effect of such constraints and find that a maximum age of one hour achieves most of the write elimination.

Combined effect

We have studied the effects of absorbing write bursts and eliminating repeated writes independently of each other. In practice, the two effects compete for buffer space. They also work together, because eliminating writes makes it possible to absorb write bursts in less buffer space. Striking a balance between the two is therefore key to effective write buffering. In this section, we investigate how to achieve this balance by appropriately setting the *highMark* and *lowMark* threshold values.

In Figure 11, we plot the write miss ratio as a function of *highMark*. As we would expect, if destage is initiated whenever a small fraction of the buffer is dirty, there is less opportunity for write cancellation. The write miss ratio is therefore high for small values of *highMark*. For our various workloads, we find that the miss-ratio curves tend to flatten beyond a *highMark* value of about 0.6. On the other hand, if the *highMark* value is set high, meaning

that destage is initiated only when most of the buffer is dirty, response time suffers because some of the writes arrive to find the buffer full and stall until buffer space becomes available. In Figure 12, we plot the average write response time as a function of *highMark*. Observe that the average write response time rises as *highMark* increases beyond about 0.8–0.9. In general, we find that a *highMark* value of about 0.6–0.9 and a *lowMark* value of less than 0.4 strike a reasonable compromise between absorbing write bursts and eliminating repeated writes. In the rest of this paper, we use as default a *highMark* value of 0.8 and a *lowMark* value of 0.2.

In Figure 13, we plot the write service time as a function of the threshold settings. Notice that the service time curves are steeper than the corresponding miss-ratio curves in Figure 11. This is because the *highMark* and *lowMark* settings also affect the efficiency with which the destage operations can be carried out. In particular, when *lowMark* is set close to *highMark*, the destage requests are issued in a continuous trickle, but when *lowMark* is set significantly lower than *highMark*, the destage operations are issued in batches and can be scheduled to be performed efficiently (see *Request scheduling* in Section 4).

A concern with background destage operations is that they may have a negative impact on the read response time. For instance, when the write buffer becomes full, background destage requests become foreground operations which may interfere with incoming read requests. Moreover, the first read request after an idle period may encounter a destage in progress. In this study, we assume that destage operations are not preemptible,

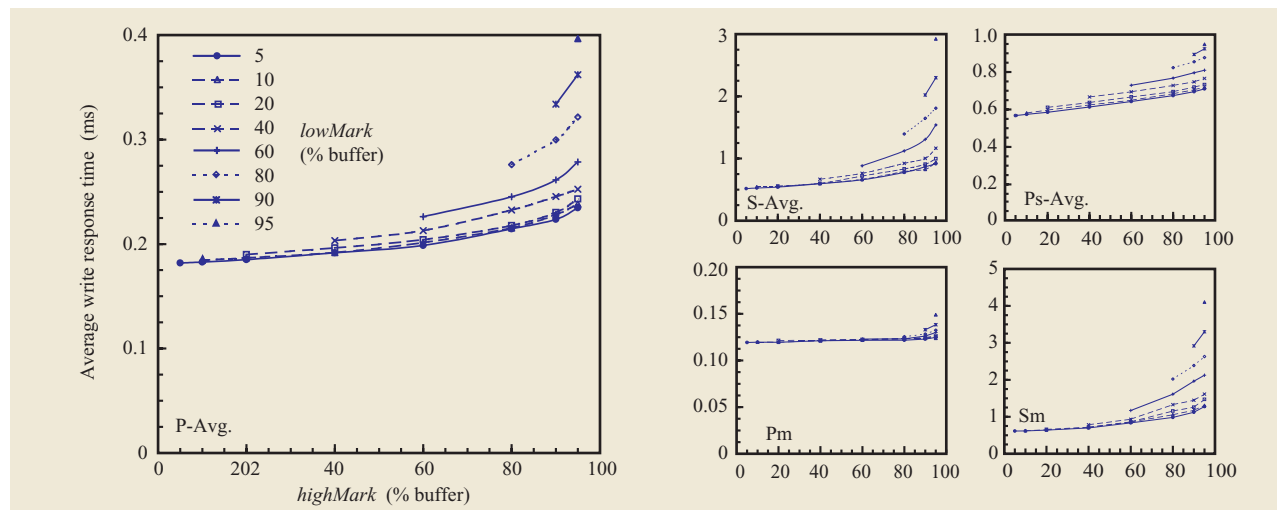


Figure 12

Effect of *lowMark* and *highMark* threshold values on average write response time in a resource-rich environment.

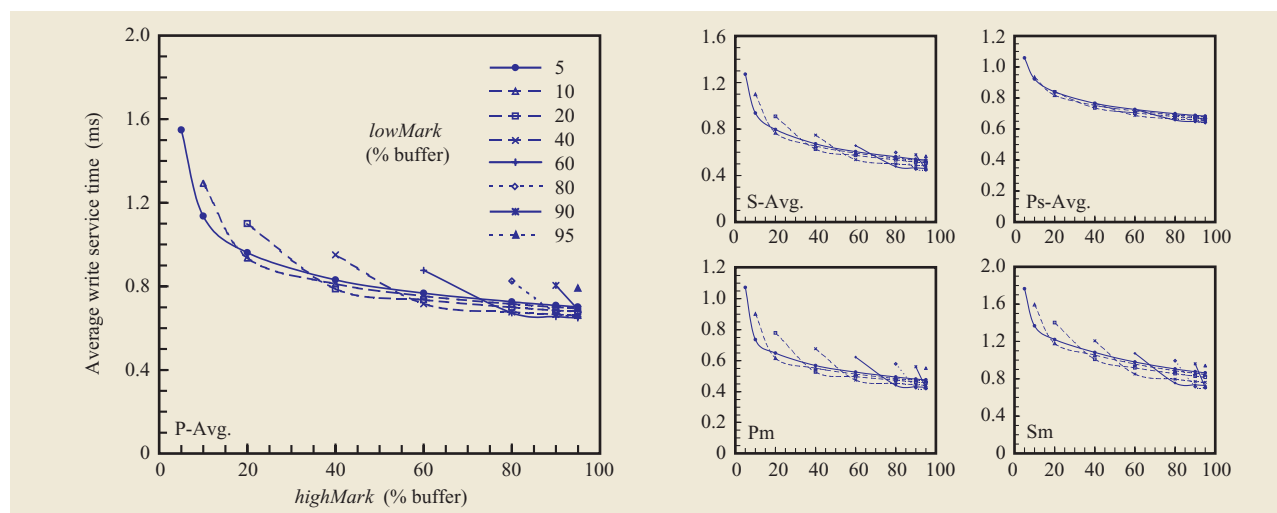


Figure 13

Effect of *lowMark* and *highMark* threshold values on average write service time in a resource-rich environment.

which is generally true at the adapter and outboard controller level because a write request cannot easily be canceled once it has been issued to the disk. We find that the read response time is not significantly affected by write buffering provided that there is some hysteresis, that is, *lowMark* is significantly lower than *highMark*. When there is no hysteresis, destage operations tend to occur after every write request and take longer because request scheduling is not effective with a small number of

outstanding requests. The chance for a read to be blocked is therefore increased. In addition, the constant trickle of destage operations may lead to disk head thrashing, because the locality of reference for destage operations (which are essentially delayed writes) is not likely to coincide with that of current read requests.

In **Table 6**, we summarize the performance benefit of write buffering. In the resource-poor environment, about 40–50% of the writes are eliminated by write buffering.

Table 6 Performance with write buffering, showing percentage of improvement over a write-through system.

	Resource-poor environment						Resource-rich environment					
	Average write response time		Average write service time		Write miss ratio		Average write response time		Average write service time		Write miss ratio	
	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(%) ⁱ		(ms)	(%) ⁱ	(ms)	(%) ⁱ	(%) ⁱ	
P-Avg.	0.227	96.9	1.41	70.9	0.606	0.227	0.218	97.0	0.700	85.6	0.424	0.218
S-Avg.	2.13	92.7	1.32	70.7	0.525	2.13	0.831	97.0	0.535	87.8	0.293	0.831
Ps-Avg.	0.646	91.6	1.05	78.2	0.520	0.646	0.695	90.9	0.681	85.9	0.412	0.695
Pm	0.190	97.7	1.30	74.2	0.598	0.190	0.123	98.5	0.474	90.5	0.332	0.123
Sm	3.48	90.1	1.57	65.2	0.572	3.48	1.16	96.7	0.855	81.0	0.380	1.16

ⁱ Improvement over write-through or no write buffer [(original value - new value)/(original value)].

Resource-poor environment: 4 MB, lowMark = 0.2, highMark = 0.8, LRW replacement, 30-second age limit.

Resource-rich environment: 0.1% of storage used, lowMark = 0.2, highMark = 0.8, LRW replacement, one-hour age limit.

The average write service time is reduced by 60–80% compared with the write-through case, while the average write response time is reduced by more than 90%. The improvement in the resource-rich environment is even more significant, with about 60–70% of the writes being eliminated and a reduction in the average write service time by as much as 90%. Note that this large reduction in write service time with a relatively small write buffer, albeit non-volatile to avoid any data loss, puts into doubt the premise of log-structured file systems [43], which are based on the idea that with large disk caches, I/O systems will have almost no reads and will be bottlenecked on writes.

Request scheduling

The time required to satisfy a request depends on the state of the disk—specifically, whether the requested data is present in the cache and where the disk head is relative to the requested data. In request scheduling [44], the order in which requests are handled is optimized to improve performance. The effectiveness of request scheduling generally increases with the number of requests that are available to be scheduled. In most systems, the maximum number of requests outstanding to the storage system can be set. The actual queue depth depends on the workload.

Request scheduling can, in principle, be performed at different levels in the storage stack (e.g., operating system, device driver, disk adapter, disk drive), provided that the necessary information is available to estimate the service times of different requests. High in the storage stack, it is difficult to make good estimates, because little information is available there. For example, modern disk protocols such as SCSI and IDE present a flat address space, so that any level above the disk drive has little knowledge of the physical geometry of the disk unless it knows the disk model number and has a table of the track and sector configurations. In addition, it is hard to predict the angular position of the disk or which requests will hit in the disk drive cache. As we have seen in the previous

sections, there are many hits in the disk drive cache, and such hits can substantially affect the effectiveness of request scheduling [14].

In this paper, we first consider scheduling the requests that miss in the cache, since the critical resource is the disk arm. We term this *arm scheduling*. Our arm-scheduling experiments assume a maximum queue depth of 8 and are based on the scheduling algorithm that has been variously referred to as shortest time first [13], shortest access time first [12], and shortest positioning time first [14]. This is a greedy algorithm that always selects the pending request with the smallest estimated access time (seek time + rotational latency). By selecting the request with the shortest access time, the algorithm tries to reduce the amount of time the disk arm spends positioning itself, thereby increasing the effective utilization of the critical resource. The algorithm can be adapted to minimize wait time by selecting the request with the shortest service time. To reduce the chances of request starvation, the requests can be aged by subtracting from each access time or positioning delay (T_{pos}) a weighted value corresponding to the amount of time the request has been waiting for service (T_{wait}). The resulting effective positioning delay (T_{eff}) is used in selecting the next request:

$$T_{\text{eff}} = T_{\text{pos}} - (W \times T_{\text{wait}}). \quad (1)$$

We refer to this variation of the algorithm as *aged shortest access time first* (ASATF) [12].

With a sufficiently large aging factor, W , ASATF degenerates to *first come first served* (FCFS). A W value of 0.006¹ is recommended in [12, 14], but the range of “good” values for W is found to be wide. In **Figure 14** we plot the average response time, including both reads and writes, and its coefficient of variation as a function of W .

¹ A value of 6 is recommended in [14], but if T_{pos} and T_{wait} are in the same units, as one would reasonably expect, the correct value should be 0.006.

The corresponding plots that consider the reads and writes separately, and the plots of the average service time as a function of W , are in [5]. For all of our workloads, the average response time is almost constant for $W < 0.03$. Observe that as W increases, the coefficient of variation for response time decreases gradually to a minimum and then increases rather sharply beyond that. The improvement in the coefficient of variation is gradual as we increase the aging factor from zero because our model, unlike those used in [12, 14], takes into consideration feedback between request completion and subsequent request arrivals so that requests are less likely to be starved. Since the variability in response time increases rather sharply for W values beyond the optimal, we err on the side of caution and select a value of 0.01 as the baseline for our other simulations. By comparing the response time at large values of W with that at small values of W , we can quantify the net effect of arm scheduling. We summarize the results in **Table 7**. In general, arm scheduling tends to have a bigger impact in the server environment. Improvement of up to 39% in average response time is seen for the server workloads. For the PC workloads, the improvement is about 15% on average. Looking at the reads and writes separately, we find that in most cases, the improvement in write response time is about two to three times that for reads. This is because writes tend to come in big bursts, so that if the destage operations are not scheduled efficiently, the write buffer is likely to become full and cause the incoming writes to stall.

Note that arm scheduling actually has two separate effects; one is to reduce the time needed to service a request, and the other is to reduce the waiting time by letting the shortest job proceed first. Observe from Table 7 that the service time improvement is more consistent across the PC and server workloads than the improvement in response time. This suggests that much of the response time improvement for the server workloads results from less waiting. Across all of our workloads, read service time is barely improved by request scheduling, while write service time is improved by 20–30% in the resource-poor environment and 35–40% in the resource-rich environment. The poor improvement for read requests is expected because the number of read requests that are outstanding and can be scheduled tends to be low [3]. The sizable improvement (up to 40%) in write service time reflects our write-buffering strategy, which is specifically designed to maintain a sizable number of outstanding destage requests so that they can be effectively scheduled.

In this section, we have so far assumed a maximum queue depth of 8 and focused on the effectiveness of arm scheduling. In practice, when there are multiple outstanding requests, the storage system cache in effect performs an *additional* level of scheduling by allowing

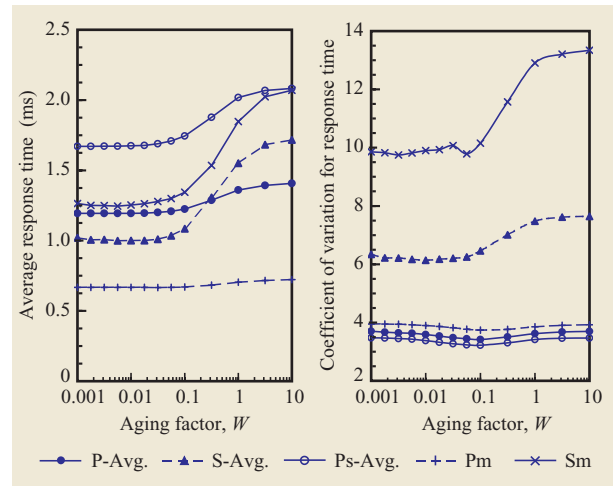


Figure 14

Effect of aging factor, W , on response time in a resource-rich environment.

subsequent cache hits to proceed. We refer to this as *cache scheduling*. In **Table 8**, we summarize the outcome of allowing multiple requests to be outstanding to the storage system. The results when reads are considered separately from writes are available in [5]. The improvement in response time reported in Table 8 includes the effect of both cache and arm scheduling. That it exceeds by only a small amount the improvement shown by arm scheduling alone (Table 7) suggests that the results from cache scheduling tend to be secondary.

Note that as the maximum queue depth is increased, the average service time is improved, but because some requests are deferred, the average response time may rise. For our workloads, a maximum queue depth of 8 is sufficient to achieve most of the benefit of request scheduling, especially the improvement in response time. In general, a deeper queue should be used for systems that are optimized for throughput, such as servers. From Table 8, with a maximum queue depth of 8, the average response time for the server workloads is improved by 30–40% in both the resource-poor and resource-rich environments, while the PC workloads are improved by about 20%. In terms of average service time, both the PC and server workloads are improved by about 20%. Breaking down the requests into reads and writes, we again find that most of the improvement is due to the writes [5].

Parallel I/O

A widely used technique to improve I/O performance is to distribute data among several disks so that multiple requests can be serviced by the different disks concurrently. In

Table 7 Performance with aged-shortest-access-time-first (ASATF) scheduling, showing percentage of improvement over first-come-first-served (FCFS) scheduling.

	Average response time						Average service time					
	All requests		Reads		Writes		All requests		Reads		Writes	
	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ
Resource-poor environment												
P-Avg.	1.51	14.2	3.34	12.8	0.227	24.6	1.74	10.8	2.22	4.03	1.41	16.5
S-Avg.	2.39	26.0	2.67	18.7	2.13	33.0	1.57	19.0	1.91	3.13	1.32	30.6
Ps-Avg.	1.96	19.0	3.83	14.4	0.646	31.1	1.52	16.4	2.18	6.08	1.05	27.1
Pm	1.24	14.4	3.14	12.6	0.190	28.1	1.63	15.4	2.23	4.24	1.30	23.8
Sm	3.43	34.8	3.37	15.1	3.48	44.7	2.06	18.8	2.67	2.71	1.57	33.6
Resource-rich environment												
P-Avg.	1.19	13.5	2.66	11.6	0.218	25.4	1.14	18.1	1.79	3.40	0.700	34.7
S-Avg.	1.00	22.3	1.20	13.3	0.831	22.6	0.689	21.6	0.886	2.68	0.535	40.9
Ps-Avg.	1.67	18.9	3.15	12.4	0.695	32.0	1.11	19.1	1.75	5.05	0.681	35.1
Pm	0.67	7.71	1.65	8.06	0.123	5.07	0.746	19.8	1.24	2.99	0.474	35.8
Sm	1.253	39.4	1.38	13.2	1.16	52.8	0.963	25.4	1.10	2.32	0.855	39.8

ⁱ Improvement over FCFS $[(original\ value - new\ value)/(original\ value)]$.
Age factor: 0.01; queue depth: 8.

Table 8 Average response and service times as maximum queue depth is increased from 1.

	Average response time								Average service time							
	Maximum queue depth								Maximum queue depth							
	2		4		8		16		2		4		8		16	
	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(ms)	(%) ⁱ
Resource-poor environment																
P-Avg.	1.68	8.59	1.56	14.8	1.51	17.8	1.52	17.2	1.99	1.44	1.79	11.1	1.74	13.7	1.70	15.8
S-Avg.	3.71	6.46	2.77	24.1	2.39	30.4	2.17	34.8	1.97	1.58	1.69	15.5	1.57	20.9	1.49	25.0
Ps-Avg.	2.29	5.83	2.08	14.4	1.96	19.3	1.99	18.6	1.79	2.89	1.59	13.9	1.52	18.0	1.46	21.0
Pm	1.43	15.0	1.31	22.7	1.24	26.6	1.25	25.8	1.97	1.61	1.71	14.3	1.63	18.6	1.57	21.6
Sm	5.32	4.41	4.02	27.7	3.43	38.3	3.12	44.0	2.52	1.76	2.19	14.5	2.06	19.8	1.95	23.8
Resource-rich environment																
P-Avg.	1.35	8.94	1.25	15.3	1.19	19.0	1.23	17.2	1.38	1.71	1.21	13.7	1.14	18.8	1.08	22.9
S-Avg.	1.70	9.42	1.23	24.9	1.00	30.4	0.889	34.6	0.895	1.72	0.747	16.3	0.689	21.2	0.635	27.4
Ps-Avg.	1.98	4.99	1.80	13.9	1.67	19.8	1.72	18.3	1.35	2.96	1.18	14.9	1.11	19.9	1.06	23.7
Pm	0.753	16.2	0.703	21.8	0.667	25.8	0.689	23.3	0.923	1.36	0.800	14.5	0.746	20.2	0.703	24.9
Sm	2.02	6.33	1.48	31.3	1.25	41.8	1.14	47.0	1.27	1.04	1.06	17.8	0.963	25.1	0.889	30.9

ⁱ Improvement over queue depth of 1 $[(original\ value - new\ value)/(original\ value)]$.
Aged shortest access time first with age factor = 0.01.

addition, a single request that spans multiple disks can be speeded up if it is serviced by the disks in parallel. The latter tends to make more sense for workloads dominated by very large transfers, specifically scientific workloads. For most other workloads, where requests are small and plentiful, the ability to handle many of them concurrently is usually more important.

In general, data can be distributed among the disks in various ways. The two most common approaches are to organize the disks into a volume set or a stripe set. In a volume set, data is laid out on a disk until it is full before the next disk is used. In a stripe set, data is divided into units called *stripe units*, and the stripe units are laid out across the disks in a round-robin fashion. In a redundant

array of inexpensive disks (RAID) [45], the stripe set is known as RAID-0. Note that the volume set is essentially a stripe set with a stripe unit that is equal to the size of the disk. A shortcoming of striping data across the disks is that, since each disk contains some blocks of many files, a single disk failure could wipe out many files. There are well-known techniques such as mirroring and parity protection to overcome this weakness, but they are beyond the scope of this study. The interested reader is referred to [16] for more details.

The choice of stripe unit has a major bearing on the performance of the storage system. A small stripe unit could result in single requests spanning multiple disks, thereby increasing the number of physical I/Os and causing many disks to be busy. More significantly, it results in many small random requests, which the disks are not very efficient at handling. Furthermore, a small stripe unit makes sequential prefetch by the disk less effective because data that appears contiguous on a disk is likely to be logically interspersed with data on other disks. On the other hand, a small stripe unit evens out the load across the multiple disks and reduces the chances that a subset of the disks will be disproportionately busy, a condition often referred to as *access skew*. For parity-protected arrays of disks, such as RAID-5, a large stripe unit would make it more difficult to do a full-stripe write, so write performance might be degraded. However, full-stripe writes are not very common in most workloads. Results of a previous study on RAID-5 striping [15] indicate that for workloads meant to model time-sharing and transaction-processing workloads, read throughput increases with stripe unit until it reaches the megabyte range, while write throughput is within 20% of the maximum at a stripe unit of 1 MB.

In **Figures 15(a)** and **15(b)**, we plot the average read and write response times for our various workloads as a function of the stripe unit, assuming that data is striped across four disks. The corresponding plots for the service time are in [5]. Observe that the response time does not rise dramatically until the stripe unit is well beyond 100 MB. This suggests that for our workloads, access skew, or imbalance in the amount of work borne by the different disks, is not a major issue unless the stripe unit is larger than 100 MB. As we increase the number of disks, it becomes more difficult to keep all of the disks equally busy, so the upward surge in response time at large stripe units is more apparent [5]. We find that a stripe unit of less than about 2 MB works well for the writes. For the reads, performance is generally good with a stripe unit in the megabyte range, with the best performance being achieved by a stripe unit of 2 MB. In the rest of this paper, we assume a stripe unit of 2 MB.

Figure 16 shows the performance achieved as we increase the number of disks across which data is striped. For all of our workloads, striping data across four disks is

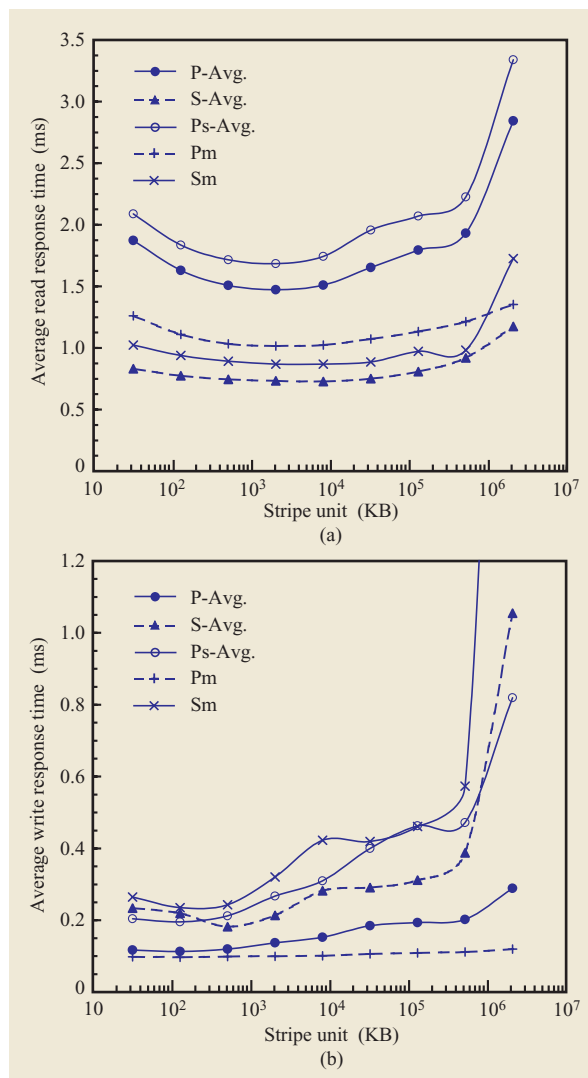


Figure 15

Average (a) read and (b) write response time as a function of the stripe unit in a resource-rich environment, assuming that data is striped across four disks.

sufficient to reap most of the performance benefit. In **Table 9**, we summarize the improvement in performance when data is striped across four disks. Overall, average read response time is improved by about 45% in the resource-poor environment and by about 40% in the resource-rich environment. Write response time is reduced much more for the server workloads than the PC workloads—as high as 94% in the resource-poor environment and 74% in the resource-rich environment. This is because, as noted earlier, writes tend to come in large bursts in the server workloads, and with more disks these writes can be handled with much less waiting time.

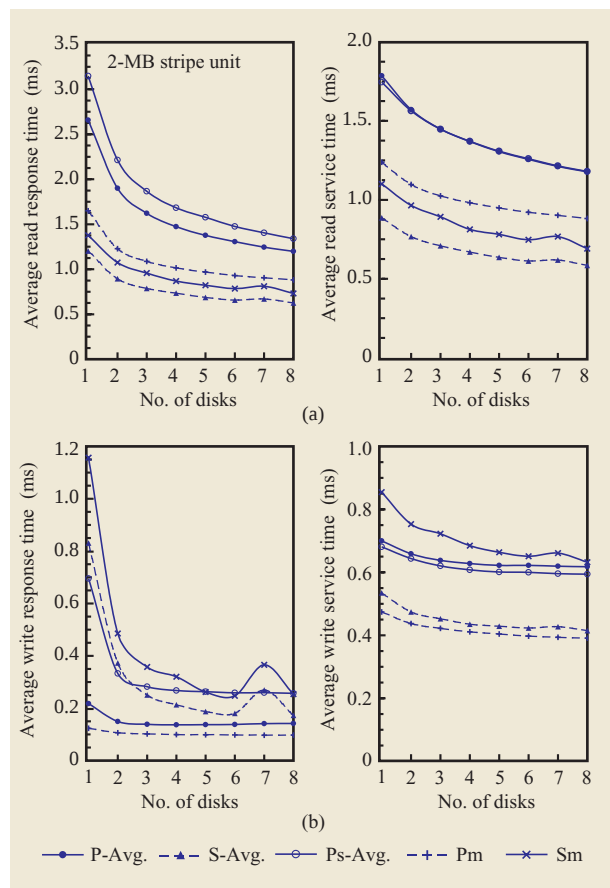


Figure 16

(a) Read and (b) write performance as a function of the number of disks across which data is striped in a resource-rich environment.

Note that the performance improvement reported in Table 9 is not due solely to less waiting for the disk arm. As more disks are used, there are more caches, prefetch buffers, and disk arm idle time with which to perform opportunistic prefetch. The combined effect of these additional resources is reflected in the decrease in miss ratio. In the resource-poor environment, the read miss ratio improves by about 20% when data is striped across four disks. The corresponding improvement in the resource-rich environment is about 15%. Recall that we define the miss ratio as the fraction of requests that requires physical I/O. Therefore, when there are multiple disks each with a cache, the miss ratio is the arithmetic mean of the miss ratio of each disk, weighted by the number of requests to that disk.

Notice further that the read service time improves by about 10% more than the read miss ratio as we increase the number of disks from one to four. This improvement in service time beyond the reduction in miss ratio is due

to less disk arm movement. When data is striped across the disks, the locality of reference is affected. For example, each of the active regions (e.g., active files) could be mapped contiguously to a different disk, in which case each of the disk arms would not have to travel far. Conversely, an active region could be distributed among the multiple disks, requiring all of the arms to move to that region. More significantly, when data is distributed across more disks of the same capacity, which is what we are doing, the total capacity of the system grows and each disk arm has a narrower range of movement. An alternative would be to compare performance using smaller-capacity disks as the number of disks increases so as to keep the total storage capacity constant, but the storage required for many of our workloads is already smaller than the capacity offered by a one-surface disk.

More generally, when only a portion of the disk capacity is used, the disk performs better because the seek distance is reduced. This effect is called *short-stroking*. To directly quantify the short-stroking effect, we return to our base configurations of using a single disk and increase the capacity of that disk by adding disk platters (recording surfaces). We discover that the service time improvement saturates when disks that are $4\times$ larger than required are used [5]. Largely in agreement with the results above, we find that short-stroking a disk that is $4\times$ larger than necessary improves the average read service time by 10–15% for our workloads. For writes, the improvement ranges from 15% to 20%. The improvement is rather low because short-stroking reduces only the seek time, which, as we shall see, constitutes only about 25% of the read response time. Moreover, because of inertia and head settling time, there is but a relatively small time difference between a short seek and a long seek, especially with newer disks.

5. Effect of technology improvement

At its core, disk storage comprises a set of rotating platters upon whose surfaces data is recorded. Typically there is a read-write head for each surface, and all heads are attached to the disk arm, so they move in tandem. This simple high-level description already suggests that there are multiple dimensions to the performance of the disk. For instance, the rate at which the platters rotate, how fast the arm moves, and how closely packed the data is, all affect, in some way, how quickly data can be read or written. Moreover, the effective performance of a disk depends on which blocks are accessed and in what order. Therefore, it is not clear what effect technology improvement or scaling in any one dimension has on real-world performance. In this section, we relate scaling in the underlying technology to the actual performance of real workloads. The goal is to quantify the real impact of improvement in each dimension

Table 9 Performance with striping across four disks, showing percentage of improvement over a single disk.

	Read						Write					
	Average response time		Average service time		Miss ratio		Average response time		Average service time		Miss ratio	
	(ms)	(%) ⁱ	(ms)	(%) ⁱ	(%) ⁱ		(ms)	(%) ⁱ	(ms)	(%) ⁱ	(%) ⁱ	
Resource-poor environment												
P-Avg.	1.72	48.0	1.56	30.1	0.333	22.8	0.105	43.7	1.34	4.75	0.596	1.62
S-Avg.	1.37	49.6	1.30	34.6	0.275	22.8	0.149	70.4	1.04	18.2	0.480	7.72
Ps-Avg.	1.91	50.1	1.56	28.6	0.350	22.5	0.149	74.6	0.915	13.4	0.503	3.50
Pm	1.77	43.7	1.66	25.5	0.364	18.7	0.102	46.4	1.26	3.14	0.577	3.52
Sm	1.93	42.7	1.91	28.5	0.385	17.7	0.223	93.6	1.13	28.1	0.495	13.4
Resource-rich environment												
P-Avg.	1.47	43.7	1.37	24.0	0.261	16.9	0.137	27.0	0.628	10.4	0.425	−0.434
S-Avg.	0.734	35.1	0.669	23.3	0.145	12.6	0.214	54.0	0.435	20.1	0.296	−0.936
Ps-Avg.	1.68	46.2	1.37	22.1	0.268	16.5	0.268	57.9	0.608	10.8	0.420	−2.15
Pm	1.02	38.5	0.981	20.7	0.195	13.7	0.100	19.4	0.411	13.3	0.333	−0.582
Sm	0.869	36.8	0.812	26.2	0.171	16.2	0.321	72.3	0.685	19.9	0.383	−0.979

ⁱ Improvement over single disk $[(original\ value - new\ value)/(original\ value)]$.

Stripe unit: 2 MB.

and establish some basic rules of thumb for designing and selecting disks.

The performance impact of technology improvement in the different dimensions is generally difficult to isolate and quantify systematically because the performance metrics with which we are familiar, such as access time, are often metrics that compound the effect of improvement in multiple dimensions. For instance, the often-quoted 10% yearly improvement in the access time of disks results from a combination of an increase in rotational speed (reduction of rotational latency), decrease in seek time due to improvement in the disk arm actuator, and smaller-diameter disks or narrower data bands, which reduce seek distance. In practice, for a given workload, the actual seek time is also affected by improvement in areal density because the head has to move a smaller physical distance to get to the data. Changes in areal density also lead to changes in storage capacity which could potentially affect the number of disks and the mapping of data to disks.

In this section, we break down the continuous improvement in disk technology into four major basic effects:

- Seek time reduction due to actuator improvement.
- Increase in rotational speed.
- Linear density improvement.
- Increase in track density.

While we do not explicitly consider discrete effects, such as changes in the form factor (e.g., 5.25-inch to 3.5-inch disk), their impact on performance can be understood

from our analysis of the basic effects. For example, a smaller form factor affects performance through the potential increase in rotational speed, decrease in seek time, and reduction in transfer rate (because of the smaller circumference of the disk). The latter is not one of the four basic effects we have identified, but it can be accounted for by using our results on the effect of linear density changes.

Note that the disk heads for the different surfaces are attached to the disk arm and move in tandem. In the past, this meant that tracks within a cylinder were vertically aligned, and no additional seek was required to read the next track in the cylinder. However, in modern disks, only one of the heads is positioned to read or write at any one time because the disk arm flexes at the high frequency at which it is operated. Therefore, when the head reaches the end of a track, there is a delay before the next head is positioned to start transferring the data. To prevent having to wait an entire revolution after a track switch, the tracks in a cylinder are laid out at an offset known as the *track-switch skew*. There is also a delay for moving the head to an adjacent cylinder, so tracks are laid out at an offset known as the *cylinder-switch skew* across cylinder boundaries. As we scale the performance of the disk, we adjust the skews to make sure that the disk does not “miss revolutions” for transfers that span multiple tracks.

Mechanical improvement

We begin by examining the improvement in the mechanical or moving parts of the disk. **Figure 17** presents the

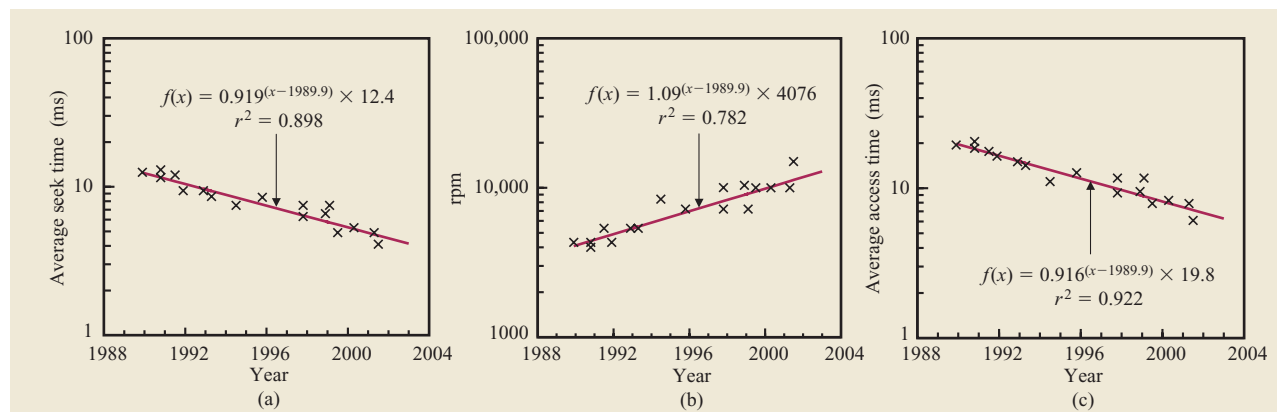


Figure 17

Historical rates of change in (a) average seek time, (b) rotational speed, and (c) access time for IBM 3.5-inch server disks.

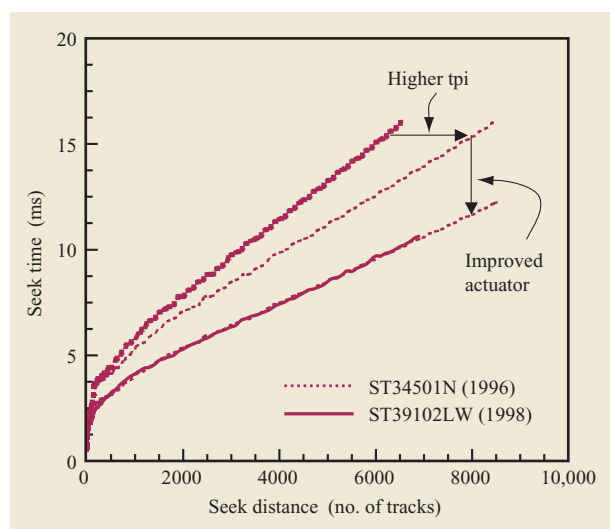


Figure 18

Changes in seek profile across two generations of a disk family (tpi: tracks per inch).

historical rates of change in the average seek time, rotational speed, and access time for the IBM family of 3.5-inch server disks. The average seek time is generally taken to be the average time needed to seek between two random blocks on the disk. The average access time is defined as the sum of the average seek time and the time needed for half a rotation of the disk. Observe that on average, seek time decreases by about 8% per year, while rotational speed increases by about 9% per year. Putting the two together, average random access performance improves by slightly more than 8% per year.

Note that the time needed to seek between two given tracks is reduced over time through both mechanical improvement, which enables the disk head to be moved more quickly, and track density increase, which reduces the physical separation of the tracks. For instance, in **Figure 18**, we show how the seek profile changes across two generations of a disk family. Beginning with the seek profile of the earlier disk, we first scale it horizontally to account for the increase in the track density. Subsequent scaling in the vertical direction results in a curve that fits the seek profile of the later disk almost perfectly. However, because average seek time is defined as the time needed to seek between two random blocks on the disk, and the time difference between a short seek and a long seek is relatively small, the observed 8% yearly improvement in the average seek time can be attributed primarily to mechanical improvement, assuming that the width of the data band remains fairly constant.

Seek time

In **Figure 19**, we plot the effect of improvement in the average seek time on the average response time for our various workloads. The corresponding plots for the average service time are similar and are presented in [5]. Note that the physical I/Os in the resource-rich environment are not exactly those in the resource-poor environment because there are different amounts of caching and write buffering in the two environments. However, it turns out that the performance effect of disk technology improvement is almost identical in both environments. We therefore present only the figures for the resource-rich environment in this paper; the largely similar plots for the resource-poor environment can be found in [5].

Besides plotting the response time improvement as a function of the improvement in average seek time [Figure 19(a)], we also show how the response time improvement varies over time, assuming the historical 8% yearly improvement in average seek time [Figure 19(b)]. To generalize our results, we fitted a curve to the arithmetic mean of the five classes of workloads. As shown in the figures, a linear function of the form $f(x) = ax$, where a is a constant, turns out to be a good fit. Specifically, we find that a 10% improvement in the average seek time translates roughly into a 4% gain in the actual average response time, and that a year of average seek time improvement at the historical rate of 8% per year results in just under 3% improvement in the average response time.

Rotational speed

Figure 20 shows how increasing the rotational speed of the disk affects the average response time for our various workloads. Observe from the figures that the improvement in average response time as a function of the increase in rotational speed can be accurately described by a function of the form $f(x) = a(1 - e^{-bx})$, where a and b are constants. Such a function suggests that as we increase the rotational speed while keeping other factors constant, the marginal improvement diminishes, so that the maximum improvement is a . Taking into account the historical rate of increase in rotational speed (9% per year), we find that a year's worth of scaling in rotational speed corresponds to about a 5% improvement in average response time.

Increase in areal density

In **Figure 21**, we present the rate of increase in the linear, track, and areal density of disks over the last ten years. Observe that the linear density has been increasing by approximately 21% per year, while the track density has been going up by around 24% per year. In the last few years areal density has increased especially sharply, so that with a least-squares estimate (no weighting), the compound growth rate is as high as 62%. If we minimize the sum of squares of the relative (instead of absolute) distances of the data points from the fitted line so that the large areal densities do not dominate ($1/y^2$ weighting), the compound growth rate is about 49%. Combining the growth rate in rotational speed and in linear density, we obtain the rate of increase in the disk data rate. This turns out to be 40% per year [5], which is dramatically higher than the 8% annual improvement in average access time. The result is a huge gap between random and sequential performance, and is one of the primary motivations for reorganizing data to improve the spatial locality of Reference [4].

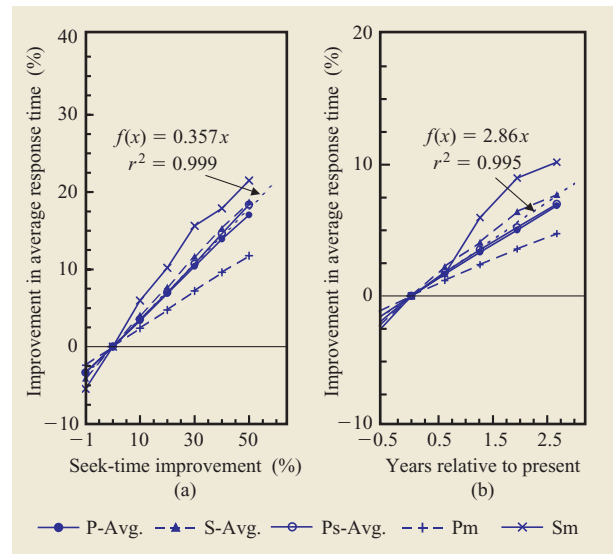


Figure 19

Effect of improvement in average seek time on average response time in a resource-rich environment: (a) Function of improvement in average seek time. (b) Function of years of improvement in average seek time at historical rate (8% per year).

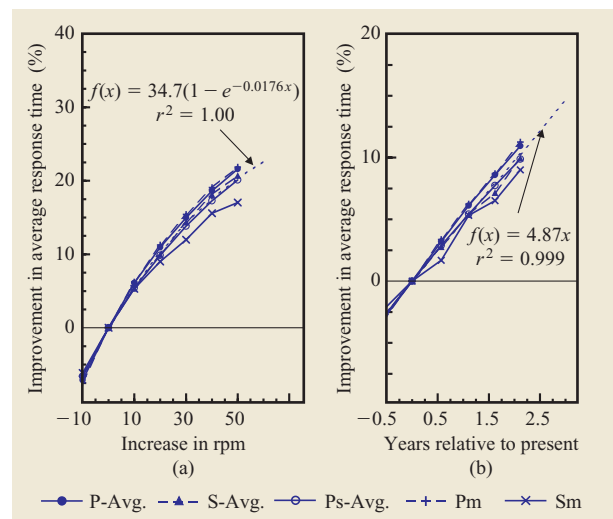


Figure 20

Effect of rpm scaling on average response time in a resource-rich environment: (a) Function of increase in rpm. (b) Function of years of rpm increase at historical rate (9% per year).

Linear density

Increasing the areal density reduces the cost and therefore the price/performance of disk storage. Areal density

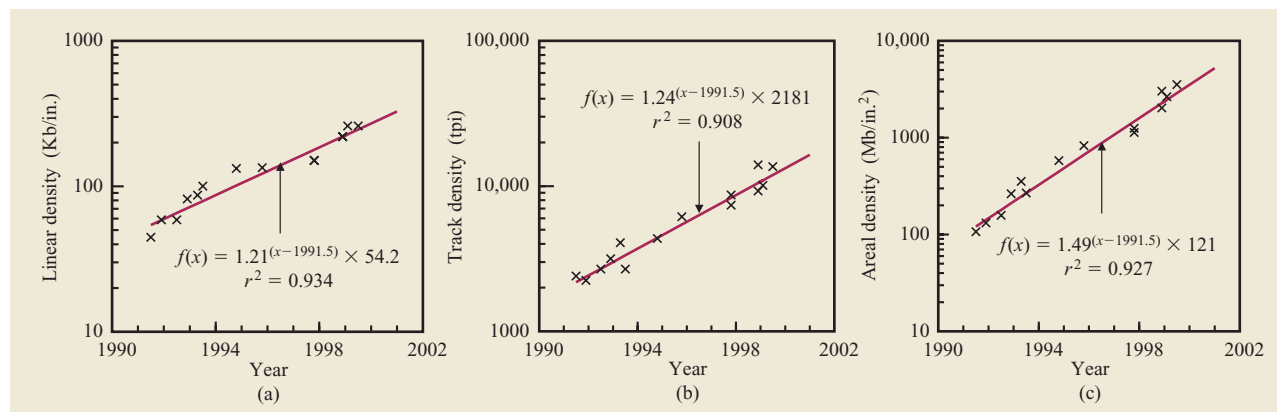


Figure 21

Historical rates of increase in (a) linear, (b) track, and (c) areal density for IBM 3.5-inch server disks.

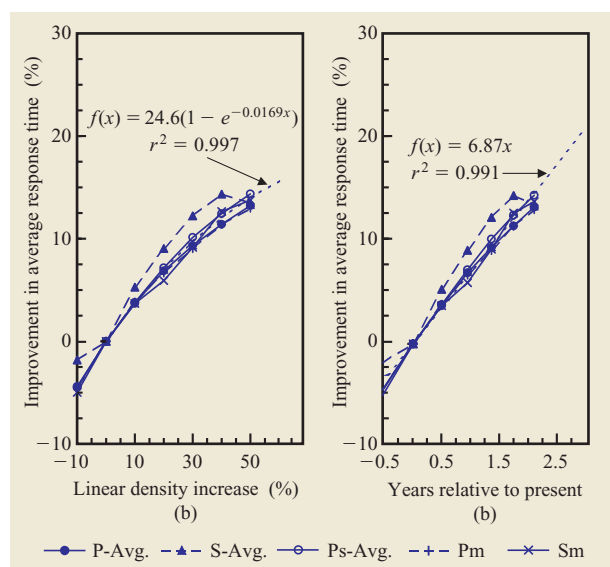


Figure 22

Effect of increased linear density on average response time in a resource-rich environment: (a) Function of increase in linear density. (b) Function of years of linear density increase at historical rate (21% per year).

improvement also directly affects performance because, as bits are packed more closely together, they can be accessed with a smaller physical movement. **Figure 22** shows how increases in the linear density reduce the average response time for our various workloads. We find that the improvement in average response time as a function of the increase in linear density can again be accurately modeled by a function of the form $f(x) = a(1 - e^{-bx})$,

where a and b are constants, and each year of linear density improvement at the historical rate of 21% per year results in a 6–7% reduction in average response time.

Notice that the S-Avg. plot in **Figure 22** shows a little dip toward the end. This slight drop in performance as linear density is increased results from the fact that the database server workload (DS1), one of the components of S-Avg., is sensitive to how the blocks are laid out in tracks because some of its accesses, especially the writes, occur in specific patterns. As linear density is increased, each track contains more blocks. In some cases, the new assignment of blocks to tracks causes consecutively accessed blocks to become poorly positioned rotationally, leading to long rotational latencies even with request scheduling. For example, consecutively accessed blocks could become arranged such that the disk head is positioned for the next access just after the target block rotates under the head. Such situations highlight the need for automatic block reorganization such as that proposed in [4].

Track density

Packing the tracks closer together means that the arm has to move over a shorter physical distance to reach the same track. This effect is similar to that of improving the average seek time, but the quantitative effect on the average response time per unit of improvement tends to be much smaller because of the shape of the seek profile. In particular, the marginal cost of moving the arm is relatively small once it is moved. In **Figure 23**, we present the effect of increasing the track density on the average response time. Observe that a year's worth of track density scaling (24%) buys only about 3–4% improvement in average response time.

Overall improvement over time

In **Figure 24(a)**, we put together the effect of mechanical improvement and areal density scaling to obtain the overall performance effect of disk technology evolution. We find that the actual improvement in average response and service times as a function of the years of disk improvement at the historical rates can best be described by an exponential function of the form $f(x) = a(1 - e^{-bx})$ where a and b are constants. However, to project outward for the next couple of years, a linear function is a reasonably good fit. Observe that for our various workloads, the average response time and service time are projected to improve by about 15% per year. The different classes of workloads have almost identical plots, which increases confidence in our result.

The rate of actual performance improvement (15%) turns out to be significantly higher than the widely quoted “less than 10%” yearly improvement in disk performance because it takes into account the dramatic improvement in areal density and assumes that the workload and the number of disks used remain constant (e.g., each PC has at least one disk) so that the disk occupancy rate is diminishing. In **Figure 24(a)** and **Figure 24(b)**, for example, the average storage-used-to-disk-capacity ratio goes from about 55% (see *Simulation model* in Section 3) to 25% after two years of areal density increase at the historical rate. In any case, we note that CPUs are doubling in speed every year or two, so the demands on the I/O system are increasing faster than the capability of the I/O system.

In order to estimate the yearly improvement in the situation where the increased capacity of the newer disks is utilized so that the disk occupancy rate is kept constant, we examine the effect of improving only the mechanical portions of the disk (average seek time and rotational speed). We find that the average response and service times improve by about 8% per year [**Figure 24(c)**]. We also explore the scenario in which only the areal density is increased [**Figure 24(b)**] and discover that the average response and service times are improved by about 9% per year. This improvement comes about because as areal density is increased, the data is packed more closely together and can be accessed with a smaller physical movement. Note that the overall yearly performance improvement, at 15%, is slightly lower than the sum of the effects of the mechanical improvement and the increase in areal density. This is because the two effects are not orthogonal. For instance, as the recording density is increased, each access will likely entail less mechanical movement, so that the benefit of having faster mechanical components is diminished.

There is often a wide disparity between the actual access time and the advertised or specified performance parameters of a disk because the specified figures are obtained under the assumption that the workload exhibits

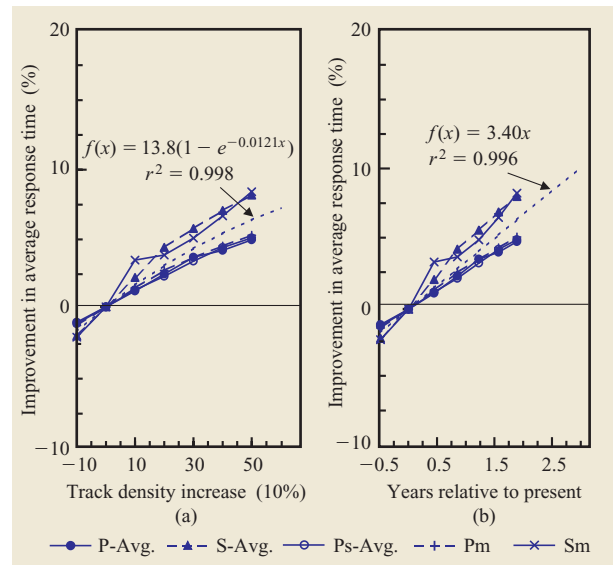


Figure 23

Effect of increased track density on average response time in a resource-rich environment: (a) Function of increase of track density. (b) Function of years of track density increase at historical rate (24% per year).

no locality. Specifically, the average seek time is defined as the time taken to seek between two random blocks on the disk, and the rotational latency is generally taken to be the time for half a revolution of the disk. In practice, there is locality in the reference stream, so we would expect the actual access time to be significantly lower. In **Figure 25**, we look at the actual average seek time and rotational latency of our various workloads as a percentage of the values specified by the disk manufacturer. As shown in the figure, the actual average seek time is about 35% of the advertised average seek time, and the average time taken for the correct block to rotate under the head is about 60% of that specified. The seek percentage decreases slightly over time because of the improvement in areal density, but the effect is not very significant. The non-monotonic nature of the rotational latency curve for S-Avg. is again due to the fact that DS1 is sensitive to the way that blocks are laid out in tracks. As the rotational speed and linear density increase over time, a poor block layout sometimes results.

To gain further insight into where a request is spending most of its time, we break down the average read response time and write service time into their components in **Figure 26**. The figure shows data for the resource-rich environment. The comparable results for the resource-poor environment are available in [5]. In the figure, the component identified as “processing” refers to the disk command processing time, which varies with the type of

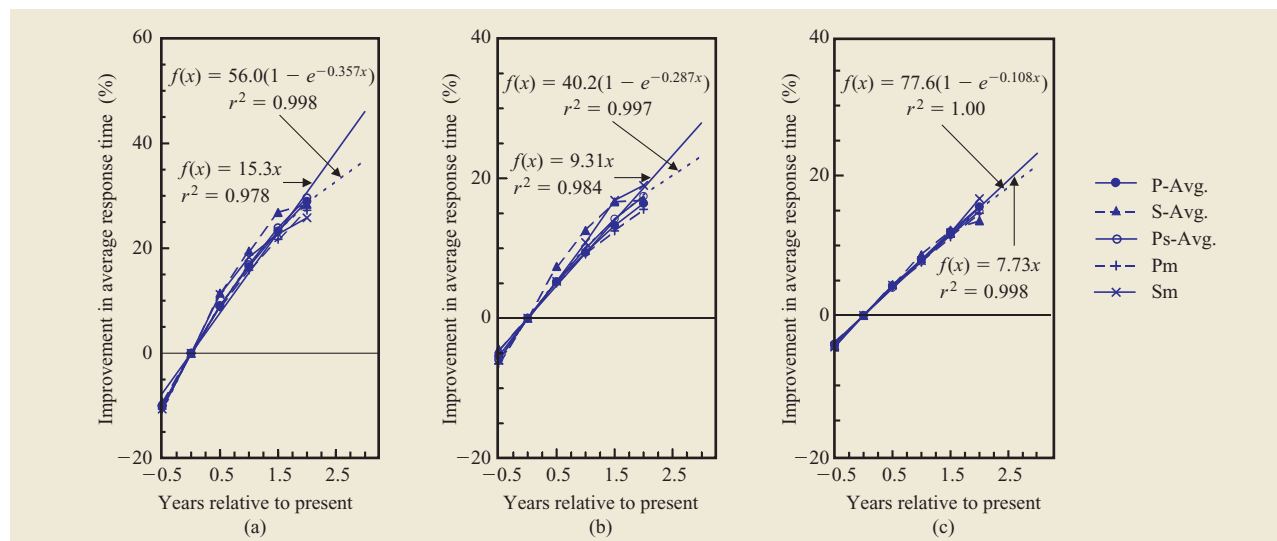


Figure 24

Improvement of average response time in a resource-rich environment as a function of years of (a) disk technology improvement; (b) areal density increase; (c) mechanical improvement; at the historical rate.

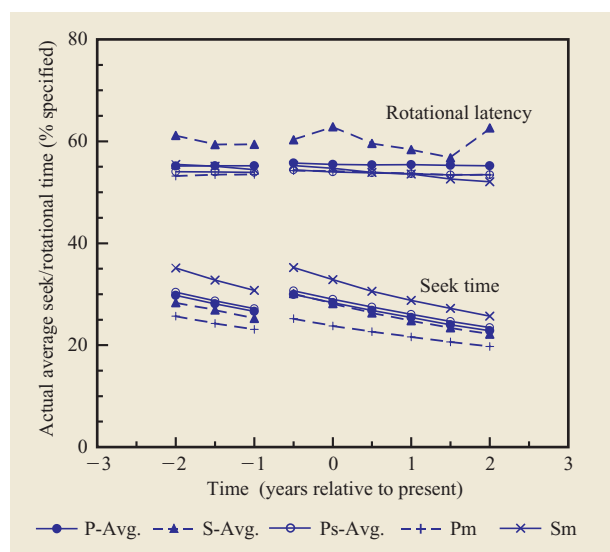


Figure 25

Actual average seek time and rotational latency as a percentage of manufacturer-specified values in a resource-rich environment.

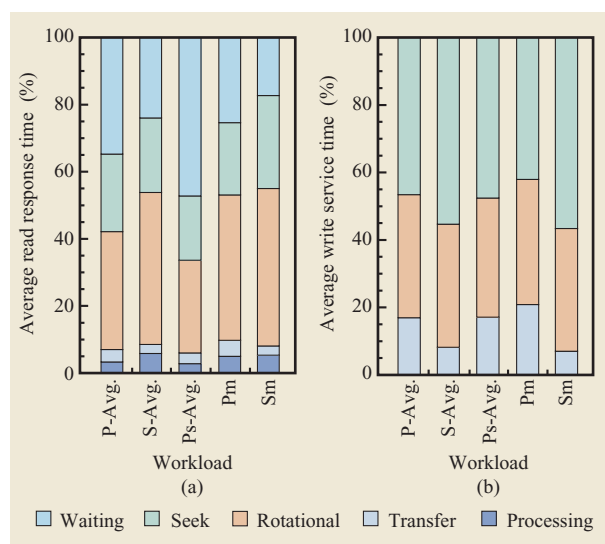


Figure 26

Breakdown of (a) average read response time and (b) average write service time in a resource-rich environment.

request (read or write) and with whether or not the previous request is a cache hit. For all of our workloads, the command processing time is not significant and averages less than 5% of the read response time. We define *waiting time*, also known as *queuing time*, as the

difference between response time and the sum of service time and processing time.

Notice that even with a 10,000-rpm disk, rotational latency constitutes a major portion (30–40%) of both the read response time and the write service time. The seek

Table 10 Performance effect of various I/O optimization techniques, showing percentage of improvement $[(time\ without\ technique - time\ with\ technique)/(time\ without\ technique)]$.

			Read			Write		
			Average response time	Average service time	Miss ratio	Average response time	Average service time	Miss ratio
Resource-poor environment								
Read caching	8 MB per disk, LRU replacement		4.49	4.14	4.45	0	0	0
Prefetching	32-KB read ahead, preemptible read ahead up to 128 KB, read any free blocks		46.6	46.1	53.0	0	0	0
Write buffering	4 MB per disk, LRW replacement, 30-s age limit		0	0	0	93.8	71.8	43.5
Request scheduling	Aged shortest access time first, age factor = 0.01, queue depth of 8		16.2	2.8	0	49.9	30.5	0
Parallel I/O	Stripe unit of 2 MB		46.8	29.5	20.9	65.7	13.5	5.96
Short stroking	4× the required storage capacity		15.9	13.6	0.3	14.6	19.4	−0.2
Resource-rich environment								
Read caching	1% of storage used, LRU replacement		37.4	36.1	35.1	0	0	0
Prefetching	Conditional sequential prefetch, preemptible read ahead up to 128 KB, read any free blocks		51.1	50.3	59.7	0	0	0
Write buffering	0.1% of storage used, LRW replacement, one-hour age limit		0	0	0	96.0	86.2	63.1
Request scheduling	Aged shortest access time first, age factor = 0.01, queue depth of 8		17.0	1.8	0	46.2	38.4	0
Parallel I/O	Stripe unit of 2 MB		40.0	23.3	15.2	46.1	14.9	−1.0
Short stroking	4× the required storage capacity		15.1	13.1	0.3	14.6	19.6	0.1

time is also very significant, accounting for about 25% of the read response time and 45% of the write service time. Note that request scheduling affects how the disk head positioning time is proportioned between seek and rotational time, especially for writes, which we issue in batches. In any case, for both reads and writes, most of the time is spent positioning the disk head. The transfer time, on the other hand, accounts for less than 5% of the read response time and only about 10% of the write service time. As the data rate continues to rise dramatically, the transfer time will diminish further. Note that the transfer time is the only time during which data is being read or written. In other words, the disk bandwidth will become less and less effectively utilized. Thus, we should consider reorganizing data to better take advantage of the available disk bandwidth [4]. Observe further that the waiting time is very significant for reads and is in fact the largest component for some workloads. This, however, does not mean that the read response time will ultimately be limited by the waiting time because improving the performance of the disk will reduce the waiting time proportionately.

6. Conclusions, summary, and synthesis

We systematically study various I/O optimization techniques to establish their actual effectiveness at improving I/O performance. Our results—based on analyzing the sequence of physical I/Os of a variety of real server and PC workloads—are summarized in **Table 10**. For each technique, the table shows the average improvement over five classes of workloads: PC workloads, server workloads, speeded-up PC workloads, merged PC workloads, and merged server workloads.

We find that the most effective approach to improving I/O performance is to reduce the number of physical I/Os that have to be performed. When designing a storage system, we would therefore first focus on caching, prefetching, and write buffering. Because caching is already performed upstream in the host, small caches in the megabyte range are not useful at the storage level. The small amount of memory in the disk drive should be designed more as a prefetch buffer than a cache that captures block reuse. Thus, increasing its size beyond the megabyte range is not very useful. If cost is not a major

Table 11 Performance effect of disk technology evolution at the historical rates, showing percentage of yearly improvement $[(original\ value - new\ value)/(new\ value)]$.

	<i>Annual rate of improvement</i>	<i>Resource-poor environment</i>		<i>Resource-rich environment</i>	
		<i>Average response time</i>	<i>Average service time</i>	<i>Average response time</i>	<i>Average service time</i>
Linear density	21	6.21	5.39	7.08	6.73
Track density	24	3.48	3.28	3.42	3.29
Areal density	49	8.58	7.97	9.31	9.07
Disk arm (seek time)	8	3.24	3.39	3.08	3.18
Rotational speed	9	5.08	5.11	5.41	5.30
Mechanical components	—	8.24	8.49	8.33	8.45
Overall	—	15.4	14.9	15.3	15.9

constraint, a large cache (of the order of 1% of the storage capacity) can be effective at the storage level. Further increasing the size of this cache is likely to improve performance, because the miss ratio continues to decrease at cache sizes that are beyond 4% of the storage used.

Our results clearly indicate that sequential prefetch is extremely effective. We highly recommend performing simple read ahead and, in more sophisticated implementations, setting the prefetch amount by conditioning on the length of the sequential run already observed. In a resource-poor environment, such as one where the storage system consists of only disks and low-end disk adapters, sequential prefetch together with caching is able to filter out 40–60% of the read requests. In a resource-rich environment, where there is a large outboard controller, only about 40% of the read requests require a physical I/O when caching and sequential prefetching are performed. The additional use of opportunistic prefetch makes a significant difference, further reducing the miss ratio to about 35–45% in the resource-poor environment and to 20–30% in the resource-rich environment. We therefore advocate that opportunistic prefetch be enabled on the disks.

The write buffer should be designed in the same spirit of reducing physical operations by allowing repeated writes to the same blocks to be eliminated. Using a LRW replacement policy, we find that 40% of the writes are eliminated by a small write buffer (less than 1 MB). For larger write buffers, we find that the write miss ratio follows a fifth-root rule, meaning that the miss ratio goes down as the inverse fifth root of the ratio of buffer size to storage used. For all of our workloads, most of the benefit of write elimination can be achieved without requiring dirty data to remain in the buffer beyond an hour. The write buffer should also be sized to absorb incoming write bursts. We recommend a write buffer size of the order of

0.1% of the storage capacity. Our results show that such a buffer can improve write response time by more than 90%.

After investing in techniques that reduce the number of physical operations, it is worthwhile to consider optimizations that increase efficiency in performing the remaining I/Os. For instance, when the writes are buffered, the remaining physical writes should be issued in batches so that they can be effectively scheduled (using shortest-access-time scheduling) and efficiently performed. In general, we should try to queue multiple requests at the disk (e.g., by setting the disk adapter queue depth to more than 1) so that the disk can optimize the order in which the requests are carried out. We observe that having a queue depth beyond 1 improves the average response time by 30–40% for the server workloads and by about 20% for the PC workloads. If data is striped across multiple disks to allow parallel I/O, we would do it with a large stripe unit in the megabyte range. By striping at such a granularity across four disks, the average read response time can be reduced by 40–45% from that of the one-disk case. We would generally not recommend short-stroking the disk, since using a disk that is four times larger than necessary results in an improvement in performance of only about 10–20%.

In addition to evaluating the various I/O optimization techniques, we also analyze how the continuous improvement in disk technology affects the actual I/O performance seen by real workloads. The results are summarized in **Table 11**, which shows the yearly performance improvement that can be expected if disk technology were to continue evolving at the historical rates. In the last ten years, the average seek time of the disk has decreased by about 8% per year, while the disk rotational speed has gone up by around 9% per year. At these rates of improvement, seek-time reduction achieves

about a 3% per year improvement in the actual response time seen by a workload, while increases in rotational speed account for around 5% per year. Together, the mechanical improvements bring about an 8% improvement in performance per year.

Increases in the recording density are often neglected when projecting effective disk performance, but our results clearly demonstrate that areal density improvement has as much of an impact on the actual I/O performance perceived by a real workload as the mechanical improvements. Historically, linear density increases at a rate of 21% per year, while track density grows at 24% per year. Such growth rates translate into a yearly improvement in the actual average response time of 6–7% and 3–4% respectively, for a combined 9% per year improvement in performance. Overall, we expect the I/O performance for a given workload with a constant number of disks to increase by about 15% per year owing to the evolution of disk technology. If we utilize the larger storage capacity of the newer disks so that the disk occupancy rate is kept constant, the yearly improvement in performance should be approximately 8%.

Because of locality of reference and request scheduling, we find that for our workloads, the actual average seek time is about 35% of the advertised average seek time for the disk, and the actual average rotational latency is about 60% of the value specified. Further analysis shows these figures to be relatively stable as disk technology evolves. We also observe that the disk spends most of its time positioning the head and very little time actually transferring data. With technology trends as they are, it will become increasingly difficult to effectively utilize the available disk bandwidth. Therefore, we must consider reorganizing data in such a way that accesses become more sequential [4].

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